Essays on Corporate Failure, Risk Pricing, and ESG Information

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When challenges grow, may strength, purpose, and hope grow stronger.

I dedicate this thesis to my family, whose love, sacrifices, and unwavering belief in me have guided every step of this journey.

This work is also for everyone who supported, inspired, and encouraged me along the way, your kindness made even the hardest moments meaningful.

Author's Declaration

I declare that this thesis is my own work and has not been submitted in substantially the same form for the award of a higher degree elsewhere. This thesis contains no material previously published or written by any other person except where references have been made in the thesis.

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Abstract

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This thesis examines how climate-related and sustainability risks shape corporate vulnerability and asset pricing dynamics in the U.S. market. It comprises three empirical studies that collectively explore the interaction between firm characteristics, environmental exposures, and financial performance, contributing to the field of sustainable finance. The first study investigates corporate failure risk in the U.S. energy sector using logit and Cox proportional hazard models. It shows that energy firms do not uniformly face higher or lower failure risk compared to non-energy contra-parts; rather, failure risk is conditional on factors such as leverage, input price volatility, and emissions intensity. The analysis highlights the relevance of environmental indicators, including ESG combined scores and CO_2 emissions, in predicting default risk. The second study examines the pricing of climate risk in asset markets, with an emphasis on state-level climate vulnerability in the U.S. market. By integrating climate transition and physical risk measures at the national and subnational level, it demonstrates that state-specific climate conditions, economic uncertainty, and temperature anomalies significantly influence portfolio returns. Ignoring state-level climate exposure leads to suboptimal asset allocation and underestimation of risk. Lastly, the third study assesses whether ESG ratings contain persistent informational value by decomposing ESG connectedness into short- and long-run components using frequency-domain methods. The results reveal horizon- and sector-dependent pricing effects, with long-term ESG components predicting future returns for both green and brown firms. Overall, the thesis provides new evidence on how climate and sustainability risks propagate through corporate distress channels, market pricing mechanisms, and long-horizon ESG information.

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If someone had told me a few years ago that I would complete a doctoral degree, I would never have believed it. This thesis is not only my work; it is the result of the support, generosity, and kindness of many people to whom I am deeply indebted.

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I still vividly remember teaching my very first Applied Econometrics class for the Master in Money, Banking and Finance at the age of 22. I was nervous, intimidated, and acutely aware of how young I was, but that experience confirmed how much I genuinely enjoy teaching and supporting students in their learning journey. Throughout the PhD, I taught many students across a wide range of subjects, from mathematics and statistics to econometrics and applied micro- and macroeconomics. Balancing several part-time jobs, a heavy teaching load, and ongoing research with the demands of the thesis was far from easy, but I managed it. I knew I needed to support myself in the UK while also helping my family in Portugal, and that responsibility became a source of strength rather than just a burden. It taught me discipline, perseverance, and the belief that, with determination and hard work, it is possible to reshape one's path and create new opportunities.

This thesis is therefore not only a milestone in my academic career, but also a reminder that circumstances can be changed with perseverance, hard work, and the support of those who believe in us. To everyone who walked even a small part of this path with me: thank you.

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Introduction

Climate change, sustainability, and environmental performance have rapidly evolved from peripheral considerations to central determinants of corporate behaviour, financial stability, and market valuation. What was once primarily framed as an ethical or regulatory concern is now widely recognised as a core economic force shaping firm risk, investment decisions, and asset prices. In particular, the transition to a low-carbon economy introduces new forms of risk, including transition risk, policy uncertainty, and technological disruption, that interact with traditional financial channels in complex and often non-linear ways. Understanding how these risks propagate through firms and markets is therefore not only an academic question, but also a critical issue for policymakers, regulators, and investors concerned with financial stability and capital allocation.

Despite a rapidly growing literature in sustainable finance, important gaps remain. Existing research often examines climate risk, corporate failure, or ESG information in isolation, and typically within static or homogeneous frameworks. This limits our understanding of how sustainability-related forces operate jointly across different layers of the financial system and how their effects vary across sectors, regions, and investment horizons. In particular, there is limited empirical evidence that integrates (i) firm-level vulnerability, (ii) market-wide pricing of climate risk, and (iii) the informational content of ESG measures into a unified framework.

This thesis addresses this gap by bringing together three empirical studies that collectively examine how sustainability, climate risk, and environmental performance shape corporate resilience, asset pricing, and information transmission in the United States economy. The central contribution of the thesis lies not only in the individual findings of each chapter, but in their integration: it develops a coherent framework in which sustainability-related risks operate through three interconnected channels, corporate failure risk, market pricing, and ESG information dynamics, while explicitly accounting for heterogeneity across firms, sectors, and time horizons.

In doing so, the thesis advances the literature in two key ways. First, it moves beyond single-channel analyses by jointly examining how climate and sustainability forces affect both firm outcomes and market equilibrium. Second, it introduces a dynamic and frequency-aware perspective, showing that sustainability risks are not static, but evolve over time and manifest differently across short- and long-run horizons. This integrated approach contributes to a more complete understanding of how the energy transition reshapes both firm-level risk and financial markets.

Chapter 1 focuses on the prediction of corporate failure risk in the U.S. energy sector and in highly energy-dependent industries. Recognising the strategic, economic, and geopolitical importance of the energy sector, and its exposure to commodity price volatility, regulatory pressure, and environmental constraints, this chapter develops a sector-tailored framework for understanding financial distress. Using survival models alongside logit analysis, and incorporating firm-level, macroeconomic, market structure, and environmental indicators, the study demonstrates that failure risk is not uniform across sectors. Instead, it is conditional on sector-specific exposures, including leverage, input price volatility, and environmental performance. By explicitly modelling time-to-failure and allowing for heterogeneous sensitivities across firm types, this chapter contributes to the corporate failure literature by integrating environmental indicators into survival analysis and highlighting the importance of sectoral heterogeneity in risk assessment.

Chapter 2 shifts the analysis from corporate outcomes to asset pricing, investigating whether and how U.S. financial markets price climate transition and physical risks. Drawing on a three-pass econometric framework following Giglio and Xiu (2021), this chapter introduces both national and state-level climate indicators to capture geographic heterogeneity in climate exposure and policy responses. This represents a key innovation relative to the existing literature, which typically relies on aggregate or national-level measures. The findings show that climate and policy risks are systematically priced, and that state-level variation plays a central role in shaping risk premia. By embedding climate risk within a richer, geographically disaggregated asset-pricing framework, this chapter contributes to the literature by demonstrating that ignoring regional heterogeneity can lead to mispricing and suboptimal portfolio allocation.

Lastly, **Chapter 3** turns to the informational content of ESG measures, addressing the well-documented concern that ESG ratings are noisy and inconsistent across providers (Berg, Fabisik, and Sautner (2021), Gibson Brandon, Krueger, and Schmidt (2021), and Berg, Koelbel, et al. (2022)). Rather than treating this noise as purely problematic, the chapter asks whether a meaningful signal can be extracted once ESG information is analysed dynamically. Using a time–frequency framework (Barigozzi, Hallin, et al. (2020)), the study constructs an aggregate measure of ESG connectedness and decomposes it into short- and long-frequency components. The results reveal that ESG contains a persistent, slow-moving component that predicts returns and firm fundamentals in a horizon- and firm-type-dependent manner. This represents a key conceptual contribution: ESG is not simply a noisy cross-sectional score, but a dynamic, systematic factor whose informational content depends on frequency and firm characteristics.

Taken together, these three chapters provide a unified contribution to the sustainable finance literature. First, they offer a firm-outcomes perspective, showing how environmental exposure and sectoral characteristics shape corporate vulnerability and failure risk. Second, they provide a market-pricing perspective, demonstrating that climate and policy risks are systematically reflected in asset prices, particularly when accounting for regional heterogeneity. Third, they contribute an information-content perspective, showing that ESG measures embed forward-looking signals once their dynamic structure is properly modelled.

Importantly, the contribution of the thesis goes beyond the sum of its parts. By linking corporate failure risk, climate risk pricing, and ESG information within a single empirical framework, the thesis shows that these dimensions are not independent, but mutually reinforcing. Corporate vulnerability reflects underlying exposure to climate and environmental risks; markets price these risks based on available information; and ESG signals act as a transmission channel through which sustainability-related information is gradually incorporated into prices and firm outcomes. This integrated perspective advances our understanding of the energy transition as a financial phenomenon, rather than solely an environmental or regulatory issue.

A further contribution of the thesis lies in its data construction and integration. The empirical analysis combines multiple data sources, including Compustat/Capital IQ firm-level data, ESG scores, macroeconomic indicators, energy market variables, and state-level climate data. This integration allows for a richer and more granular analysis, but also presents practical challenges. In particular, ESG data are subject to measurement error and cross-provider inconsistency; climate indicators vary in availability and comparability across states; and combining firm-level and macro-level datasets requires careful alignment in both time and frequency. Additionally, the inclusion of inactive firms to address survivorship bias introduces further complexity in defining failure events and ensuring data consistency over time.

These data limitations have important implications for interpretation. While the results are robust across multiple specifications, they should be understood as conditional on the available measures of ESG, climate exposure, and firm characteristics.

Measurement error in ESG scores may attenuate estimated effects, while limited historical availability of certain climate variables may constrain the analysis of longer-term dynamics. Moreover, the focus on U.S. firms, while providing a rich institutional setting with significant heterogeneity, may limit the generalisability of the findings to other regions with different regulatory and market structures.

Across the thesis, a consistent message emerges: sustainability and climate dynamics are not moral accessories to financial analysis; they are fundamental determinants of performance, stability, and valuation. However, their effects are inherently heterogeneous and dynamic. They vary across sectors, depend on institutional and geographic contexts, interact with firm strategies, and evolve over different investment horizons. By combining survival modelling, geographically granular asset-pricing techniques, and frequency-domain analysis of ESG information, this thesis provides a comprehensive and empirically grounded framework for understanding how sustainability considerations are increasingly embedded in modern financial systems.

Chapter 1

Corporate Failure Prediction in the U.S. Energy Sector: A Survival Analysis Approach

Abstract

Are energy firms more prone to corporate failure than non-energy firms? What firm-specific, macroeconomic, and environmental factors significantly influence the failure risk of energy firms? This paper investigates the risk of corporate failure in energy and highly dependent energy firms compared to non-energy counterparts in the U.S. through a logit and survival analysis technique using the Cox proportional hazard model. Our findings reveal that U.S. energy firms do not exhibit a uniformly higher or lower failure risk compared to non-energy firms. Instead, the failure risk for energy firms is influenced by specific factors. Energy firms face distinct challenges related to capital structure and input costs, making their failure risk more context-dependent compared to non-energy firms. They are more prone to failure due to financial leverage and volatility in input prices, but less affected by the size-related risks compared to non-energy firms. The study also highlights the predictive power of the ESG score indicator and CO2 emissions for corporate failure. Although both energy and non-energy firms are sensitive to accounting and environmental indicators, there are notable differences in the magnitude and direction of these sensitivities between the firm types.

1.1 Introduction

The prediction of corporate failure has long been a central concern in finance and economics, particularly for sectors facing high volatility and systemic importance. In recent years, the U.S. energy sector, spanning producers and energy-intensive firms, has encountered escalating financial pressure driven by geopolitical shocks, commodity price volatility, regulatory changes, and the growing imperative for environmental sustainability. These challenges have intensified the need for a sector-specific framework to assess corporate failure risk.

This paper makes a novel contribution by developing a tailored corporate failure prediction model for U.S. energy and highly energy-dependent firms, contrasting their risk profiles with those of non-energy firms. Using a comprehensive dataset covering both active and inactive firms from 2010 to 2022, we apply survival analysis following Pappas et al. (2017), specifically the Cox proportional hazard model, alongside logit regressions, incorporating firm-level financials, macroeconomic indicators, market structure variables, ESG combined scores and CO_2 emissions. Our goal is to capture the unique risk dynamics of this sector, addressing a key gap in the literature identified by Doumpos et al. (2017), among others.

Our findings reveal that, contrary to prior assumptions, U.S. energy firms exhibit a lower risk of failure than non-energy firms when controlling for key financial, environmental, and macroeconomic variables. These results are consistent across both logit and Cox proportional hazard models. Moreover, we find that energy firms are less sensitive to size-related risks but more exposed to input price volatility, particularly uranium prices. ESG performance and firm-specific indicators play a significant role in shaping hazard rates across both sectors, highlighting the importance of integrating sustainability metrics into failure prediction frameworks.

To study the risk of corporate failure, it is essential to analyse a comprehensive set of financial and non-financial indicators. Firm-specific variables such as size, cash flow, profitability, liquidity, leverage, and market capitalization remain central to default prediction models. According to Doumpos et al. (2017), characteristics like firm age, debt burden, and business activity significantly affect the likelihood of failure. Core financial indicators, including total liabilities, asset base, capital expenditures, pre-tax income, and various measures of solvency (e.g., debt ratios, free cash flow, and return on equity), continue to be strong predictors of distress.

Beyond firm-level metrics, macroeconomic conditions play a critical role. Liu (2004) and Giesecke et al. (2011) highlight that interest rates, inflation, GDP growth, stock return volatility, and credit conditions affect both short- and long-term corporate default risk.

In light of these insights, our model incorporates macroeconomic indicators such as annual GDP growth, inflation, and energy commodity prices (e.g., oil and uranium). We also consider market concentration using the Herfindahl-Hirschman Index (HHI)[1], which captures systemic risk from dominant players, aligning with the "too-big-to-fail" hypothesis. Additionally, the Investment Freedom Index[2] from the Heritage Foundation is used to proxy institutional and regulatory conditions that influence firms' operational flexibility.

Finally, consistent with recent literature, we model corporate failure risk as a function of both firm-level characteristics and time-varying macroeconomic and institutional factors. Rather than relying on conventional pooled distress models that impose homogeneous effects across firms, our empirical framework explicitly allows for heterogeneity in failure dynamics across sectors and over time. This is implemented through interaction terms between sectoral indicators (e.g., energy vs. non-energy firms) and key covariates, as well as through sector-specific estimations and time-varying regressors within both the logit and survival models. By doing so, we relax the restrictive assumption of constant marginal effects and capture differential sensitivities to financial, macroeconomic, and environmental shocks. This approach provides a more flexible and accurate representation of the determinants of corporate failure risk across heterogeneous firm groups.

Building on this perspective, it is equally important to recognize that failure risk is multifaceted (Pappas et al. (2017)), encompassing a variety of dimensions such as liquidity risk, credit risk, operational risk, and solvency risk. These risk types may interact differently across sectors, implying that energy firms could face distinct survival probabilities relative to non-energy firms. Given the sector's exposure to input price volatility, regulatory uncertainty, and environmental pressures, it becomes crucial to examine whether energy companies are inherently more or less likely to experience corporate failure compared to their non-energy counterparts.

We compile and analyse a comprehensive dataset comprising both active and inactive U.S. firms from 2010 to 2022, covering a wide spectrum of the energy ecosystem, including producers and users of energy, as well as firms highly dependent on energy consumption. Rather than limiting the scope to a single sub-sector, our analysis spans oil, gas, utilities, and extends to energy-intensive industries such as manufacturing,

[1]The HHI is computed as the sum of squared normalized market shares based on total assets, ranging from 0 to 1.

[2]https://www.heritage.org/index/investment-freedom

transportation, and warehousing. This broader perspective enables us to examine how energy exposure affects financial resilience across different business models. To further enrich our framework, we incorporate data from energy and commodity markets, including fluctuations in oil and uranium prices, offering a more granular understanding of the link between energy dependence and financial distress.

Given the longstanding concern in economics and finance about the causes and consequences of corporate failure, predicting firm-level distress remains a critical area of study. Corporate failure is broadly defined as a firm's inability to meet its financial obligations, encompassing a spectrum from technical insolvency to formal bankruptcy proceedings. Understanding the dynamics that lead to such outcomes is essential, not only for internal governance and risk assessment, but also for safeguarding market stability, supporting economic growth, and protecting broader societal welfare.

A wide range of stakeholders, including firms, financial institutions, investors, and regulators, have a vested interest in identifying and mitigating corporate failure risk. Accurate prediction models play a vital role in enabling proactive risk management and informed strategic decision-making. By enhancing our understanding of the mechanisms driving firm distress, particularly in sectors with complex and evolving risk exposures like energy, this research contributes to more effective governance practices and supports the development of policy tools aimed at fostering financial system resilience.

Despite substantial research on corporate failure prediction in sectors such as banking (Pappas et al. (2017)) and manufacturing, a notable gap remains in the context of the energy and energy-dependent sectors. The U.S. energy market's distinct features, its heavy regulation, market concentration, and exposure to volatile commodity prices, complicate standard predictive modelling and underscore the need for a sector-specific approach. While studies like Capece, Di Pillo, and Levialdi (2013) and Halkos and Tzeremes (2012) have assessed financial performance in energy firms, and Pätäri et al. (2014) has explored links between sustainability and performance, limited work directly addresses corporate failure and financial distress in this sector. Some contributions, such as Arslan-Ayaydin and Thewissen (2016), consider environmental aspects, but a comprehensive, predictive framework is still lacking. Earlier assessments of climate impacts on energy demand (e.g., Crocker and Ferrar, 1976; Linder et al., 1989; Smith and Tirpak, 1989; Nordhaus, 1991; Cline, 1992; McKibbin and Wilcoxen, 2002) largely relied on qualitative or survey-based methods. This study is the first to quantitatively explore corporate failure within U.S. energy and energy-dependent firms over a broad time horizon, responding to calls for a more interdisciplinary and data-driven approach to understanding financial stability in this critical sector (Safarzyńska and Bergh (2017)).

The U.S. energy sector occupies a unique position in the global economy, not only due to its scale and technological advancement, but also because it represents a concentrated nexus of macroeconomic exposure, financial leverage, geopolitical sensitivity, and climate transition pressures. This combination makes it a particularly relevant setting for analysing firm-level risk dynamics and broader systemic vulnerability. The sector's importance extends beyond its economic contribution, as disruptions within energy markets can propagate across industries and affect overall financial stability.

Structurally, the U.S. energy system is characterized by significant domestic resource development, technological innovation, and a high degree of energy independence (*U.S. Energy Information Administration (EIA)* (n.d.), 2021). Compared to Europe, the U.S. relies less on energy imports and benefits from a diversified energy mix that includes both fossil fuels and an expanding share of renewables. Advances in hydraulic fracturing, horizontal drilling, and renewable technologies have further reinforced its energy security (*International Energy Agency (IEA), 2022* (n.d.)). At the same time, high energy demand, driven by a large population, extensive industrial activity, and elevated per capita consumption, amplifies the sector's macroeconomic relevance. In 2021, the U.S. was the world's second-largest energy producer, supported by record natural gas output and continued growth in solar and wind energy.

Figures A.1(a) and A.1(b) (see Appendix A.1) further illustrate the central role of the U.S. in global energy consumption and carbon emissions. In 2023, North America, led by the U.S., consumed 117 exajoules of primary energy, second only to the Asia Pacific region. While China dominates regional consumption, the U.S. remains the largest single-country energy consumer and has made notable progress in renewable adoption. However, its carbon intensity per capita remains higher than that of European economies, reflecting ongoing trade-offs between economic activity and environmental performance.

These structural features and global linkages underscore the importance of studying the U.S. energy sector not only as an industry, but as a critical component of the broader financial and economic system. Energy firms operate under conditions of pronounced uncertainty, facing volatile commodity prices, evolving regulatory frameworks, and increasing pressure to transition toward more sustainable business models. Existing research highlights that sector-specific factors, such as energy network quality, market openness, and environmental performance, play a key role in shaping financial outcomes and distress risk (Doumpos et al. (2017); Growitsch, Jamasb, and Pollitt (2009); Arslan-Ayaydin and Thewissen (2016)).

Against this backdrop, this study provides a tailored analysis of corporate failure risk in U.S. energy and energy-dependent firms. By integrating accounting data, energy-specific indicators, macroeconomic variables, and environmental factors, we develop a comprehensive and sector-sensitive risk assessment framework. This approach captures the complex interplay between financial structure, market conditions, and transition-related risks, offering new insights into the determinants of firm survival in one of the most strategically important sectors of the economy.

Moreover, the comparative analysis with non-energy firms enriches the understanding of how the risk landscape differs across sectors, providing benchmarks and reference points crucial for strategic decision-making. As energy companies navigate through volatile market conditions and evolving regulatory landscapes, having a nuanced understanding of their specific failure risk profiles becomes instrumental. This research serves as a guide for informed risk management strategies tailored to the intricacies of the U.S. energy and highly dependent energy sectors, fostering resilience and sustainable growth.

Furthermore, investors are increasingly attentive to the environmental performance of energy firms, particularly in the wake of high-profile environmental disasters. Heflin and Wallace (2017) examine the role of environmental disclosures in mitigating shareholder losses during such events, using the BP oil spill, the largest marine oil spill in history, as a case study. Their findings indicate that firms with more comprehensive environmental disclosures tend to experience smaller declines in shareholder wealth and are better prepared to manage regulatory and disaster-related costs. Similarly, Smolarski and Vega (2013) highlight the substantial economic and political risks faced by energy firms, underscoring the sector's sensitivity to both environmental events and geopolitical developments.

Recent literature further emphasizes that environmental and climate-related risks are increasingly priced by financial markets. For instance, Bolton and Kacperczyk (2021) document a carbon risk premium, indicating that firms with higher emissions are subject to distinct valuation dynamics, while N. Pankratz, R. Bauer, and Derwall (2023) show that climate-related risks materially affect firm performance and investor expectations. In parallel, ESG considerations influence both firm performance and financing conditions, with implications for cost of capital and corporate resilience (Lins, Servaes, and Tamayo (2015)). These insights are particularly relevant for the energy sector, where environmental exposure and transition risks are inherently pronounced.

Beyond disaster risk, environmental performance also influences operational outcomes. Cantore, Calı, and Velde (2016) find that improved energy efficiency is positively correlated with productivity and technological advancement, particularly in developing economies. Meanwhile, Halkos and Tzeremes (2012), focusing on the renewable energy sector in Greece, identify return on equity, return on assets, and the debt-to-equity ratio as key financial performance drivers. Collectively, these studies underscore the strategic value of environmental responsibility and efficiency in enhancing both firm resilience and long-term economic performance.

This study adopts a pertinent approach to address the unique challenges in predicting corporate failure within the U.S. energy and highly dependent energy sectors. Traditional methodologies, such as statistical multivariate analysis, Merton's distance-to-default model, and z-score measures (Doumpos et al. (2017), Capece, Di Pillo, and Levialdi (2013), Halkos and Tzeremes (2012), Pätäri et al. (2014)), encounter limitations in accurately capturing the intricate risk landscape of the energy and highly dependent energy sectors. The distinctive characteristics of this industry, including heavy regulation, diverse company sizes, and complex influencing factors, necessitate a more nuanced methodology.

Against this backdrop, this study provides a tailored analysis of corporate failure risk in U.S. energy and energy-dependent firms. We develop an integrated empirical framework that combines firm-level accounting data with macroeconomic variables, commodity price indicators, market structure measures, and ESG-related factors. This approach captures the multidimensional drivers of failure risk, including financial flexibility (Fahlenbrach, Rageth, and Stulz (2021)), exposure to systemic conditions (Campbell, Hilscher, and Szilagyi (2008)), and the role of time-varying covariates in default prediction (Duffie, Saita, and K. Wang (2007); Shumway (2001)).

What sets this study apart is its focus on time-to-failure data, a critical aspect often overlooked in traditional models. By delving into the temporal dimension of failure risk, this research enhances its ability to identify distinct failure risk profiles associated with different firm sectors, offering a more nuanced understanding of the dynamics influencing corporate failure.

Finally, growing investor attention to environmental performance reinforces the relevance of incorporating ESG and climate-related factors into failure prediction models. Evidence shows that firms with stronger environmental disclosures and social capital are better able to withstand adverse shocks and mitigate value losses during crises (Heflin and Wallace (2017); Smolarski and Vega (2013); Lins, Servaes, and Tamayo (2015)). Similarly, improvements in energy efficiency and sustainability practices are associated with enhanced productivity and long-term performance (Cantore, Calı, and Velde (2016); Halkos and Tzeremes (2012)).

In contrast to widely used z-score measures, which struggle to distinguish between different types of firms and lack information about the actual failure event, this research champions discrete hazard models. The findings reference previous research highlighting the superior predictive capabilities of discrete hazard models, especially when combined with macroeconomic indicators (Shumway (2001)). The dynamic hazard models employed in this study contribute to more accurate predictions of U.S. corporate bankruptcies by considering the duration of a firm's risk of failure, incorporating panel data, and generating more reliable out-of-sample forecasts.

In summary, this research adopts a tailored approach to corporate failure prediction within the U.S. energy and highly dependent energy sectors. By systematically addressing the industry's specific challenges and incorporating a diverse set of factors, the study not only offers a more robust and nuanced understanding of failure risk but also contributes significantly to the advancement of predictive modelling methodologies.

Our analysis also uncovers that several factors exhibit varying sensitivities between energy and non-energy firms, reinforcing the notion of distinct failure risk profiles. For both energy and non-energy firms, the risk of failure is particularly sensitive to firm-specific indicators and the ESG combined score, underscoring the importance of incorporating these factors into corporate failure prediction models. Firm characteristics significantly influence hazard rates, with a substantial portion of the variation in failure risk attributed to these characteristics. Noteworthy differences emerge between the two sectors regarding the magnitude and direction of these sensitivities. For instance, both energy and non-energy firms experience increased failure risk with rising uranium prices. For energy firms, especially those in the nuclear sector, high uranium costs critically affect profitability and operational stability, demonstrating the substantial impact of volatile input prices on their financial health.

Our findings further reveal that the business models of energy and non-energy firms contribute to their distinct failure risk profiles. U.S. energy firms do not show a uniformly higher or lower failure risk compared to non-energy firms; rather, their risk is influenced by specific factors. Energy firms face unique challenges related to capital structure and input costs, making their failure risk more context-dependent. They are particularly vulnerable to financial leverage and input price volatility but are less affected by size-related risks than non-energy firms.

The subsequent sections of the paper will follow this structure: Section 2 will detail the methodology used, Section 3 will outline the main variables, data sources, and descriptive statistics, Section 4 will present empirical results, and Section 5 will provide the concluding remarks.

1.2 Methodology

A wide range of corporate failure prediction models have been developed using both traditional statistical techniques and modern machine learning approaches. The choice of methodology typically depends on data availability, model complexity, interpretability, and the desired level of predictive accuracy. Early models often relied on financial ratio analysis, such as the current ratio, debt-to-equity ratio, and return on assets, to assess firm-level distress. Statistical methods like logistic regression and discriminant analysis remain widely used due to their simplicity and interpretability. More recently, machine learning algorithms, including decision trees, random forests, and support vector machines, have been employed to capture complex non-linear relationships and improve predictive performance. These models offer promising results, particularly when large and high-dimensional datasets are available.

Beaver (1966), pioneer in terms of corporate failure prediction models with financial ratios, developed a univariate discriminatory model analysis, using several financial ratios, selected using dichotomous classification tests. Authors such as Beaver (1966), Moses and Liao (1987) used risk index models to predict failure, based on intuitive and simple point systems, centred on different ratios. Altman (1983) introduced a statistical multivariate analysis technique (MDA) to the problem of estimated a z-score model and company failure prediction. Most MDA studies used a linear MDA model, but quadratic MDA has also been applied. According to Pappas et al. (2017), the survival analysis is a more flexible method to analyse the risk of failure than z-scores (proxy to default or insolvency risk) or Merton's distance-to-default models. Therefore, we applied a logit specification of this methodology in our research.

1.2.1 Survival Analysis

The survival analysis enables us to determine the expected time-to-failure. Furthermore, this analysis enables us to recognize the continuous-time nature of the failure probability. Lastly, by using the survival function the complete and censored lifetime data of the firms are easily accommodated. This last property implies that the survival analysis of the firms' failure risk takes in consideration the fact that the observation period might not represent the firms' entire lifetime. The survival models account for the right-censored data (Lemeshow, May, and Hosmer Jr (2011)).

The analysis on banking failure risk literature makes use of the semi-parametric Cox proportional hazard model[3] (Cox (1972)). The Cox proportional hazard model estimates

[3]The Cox proportional hazards model is a robust method in survival analysis that addresses

the effects of different covariates influencing the times to failure (Cox (1972)). This is a distribution-free approach; therefore, useful in our analysis. The Cox model has been first used in medicine (e.g., survival time of patients under treatment) and engineering (e.g., time-to-failure of materials), and more recent literature, such as Molina (2002), Cole, Q. Wu, et al. (2009) use the Cox model to assess conventional bank failure (Pappas et al. (2017)).

By using the Cox proportional hazard Model, where $T \epsilon \left[0, \ \infty\right[$ is defined as the time-to-failure that represents a random variable, assuming the probability density function ($f(t)$) and the cumulative density function ($F(t)$) defined as followed,

$$f\left(t\right) = \ -\frac{dF(t)}{dt} \tag{1.1}$$

$$F\left(t\right) = \Pr\left(T \leq t\right) \tag{1.2}$$

The cumulative density function represents the probability that the event of interest occurs earlier than time t. The survivor function $S(t)$ is defined as the probability of surviving beyond year t, and the hazard function (hazard rate), sometimes called instantaneous failure rate, $h(t)$, is defined as the instantaneous risk of firms disappearance in year t conditional on its existence up to time t, this means, the probability of the "event" of interest occurs in the next instant, given survival to time t. These two functions, can be defined, respectively, as

$$S\left(t\right) = 1 - F\left(t\right) = \Pr\left(T > t\right) \tag{1.3}$$

$$h(t) = \lim_{dt \to 0} \frac{\Pr(t \leq T \leq t + dt)}{dt \times S(t)} = \frac{f(t)}{S(t)} \tag{1.4}$$

Assuming, that the hazard rate must be non-negative but non-constrained, $h(t) \geq 0$, providing a time-varying risk of firm failure.

Moreover, by using actual data on whether a firm failed over the observation window and the time when the failure occurred, we use the unconditional Kaplan and Meier (1958) estimator of the survivor function $S(t)$. The null hypothesis is, described as the unconditional survival rates for the different firm types (energy firms vs. non-energy

heterogeneity among subjects by incorporating multiple covariates to explain variations in hazard rates. It estimates hazard ratios for each covariate, assuming that these ratios are constant over time, which allows for controlling differences in baseline hazard rates. While the model does not directly account for unobserved individual heterogeneity beyond the included covariates, it adjusts for various predictors' effects, thereby reducing the influence of unobserved variability. This approach provides a nuanced understanding of survival differences among groups by isolating the impact of observed variables on the risk of the event.

firms), is tested using a long-rank test statistic with a $\chi^{\mathbf{2}}_{(\mathbf{1})}$ distribution. The null hypothesis in this context examines whether there exists a significant distinction in the unconditional survival rates between various types of firms, specifically U.S. energy firms versus non-energy firms. Within this framework, the alternative hypothesis essentially posits the absence of an effect or distinction in the survival rates among different types of firms. Put more simply, it implies that there is no significant contrast in the survival rates between energy firms and non-energy firms. Therefore, this hypothesis serves as a means to validate our research question.

Additionally, using the same data on firm failure combined with the data on vector of firm-specific attributes, energy-specific attributes, environmental related aspects, and U.S.-specific effects, denoted by x, we can estimate the Cox proportional hazard Model that is formalized as followed,

$$h(t|x(t)) = h_0\,(t)\,e^{\beta' x(t)} \tag{1.5}$$

Where β is a k x 1 vector of unknown parameters that represents the sensitivities of interest; $x\,(t)$ is a k x 1 matrix of variables for firms accounting data, macroeconomic and business indicators, energy-related data, and environmental specific effects. $\mathbf{h_0}\,(\mathbf{t})$ corresponds to the baseline hazard rate that is assumed to be the same for all the firms at time t; if the covariates have been demeaned, this rate can be interpreted as the hazard rate of an "average" firm in the population. Additionally, $\mathbf{h}(\mathbf{t}|\mathbf{x}(t))$ represents the hazard rate and can be defined as the failure event rate that a firm fails any time within year t, conditional on its accounting data, macroeconomic and business, energy-related specific attributes, and environmental aspects at the start of year t. By using the maximum likelihood estimation of the Cox model, we do not need to specify a particular distribution for $h_0\,(t)$, to obtain the estimators $\hat{\beta}_1, \ \ldots \ , \hat{\beta}_k$. A value for $\hat{\beta}_k > 0$, can be interpreted as a rise in the k^{th} covariate x_k increases the failure risk and decreases the firm survival time. The exponential coefficients $e^{\hat{\beta}_k}$ represent the hazard ratio, and $100 \ \times \ (e^{\hat{\beta}_k} \smile 1)$ gives the expected percentage increase in failure risk for a one unit increase in the k^{th} covariate. The log-likelihood function that is maximized to estimate the β's, is a partial log-likelihood function that is confined only to the failure times and does not consider the no-failure times. Therefore, the only information that enters in the log-likelihood are the values of the covariates for both the failed and non-failed firms at the end of the sample years that immediately precede each of the observed failure times $x\,(t_1)\,, \ \ldots, \ x\,(t_j)\,, \ \ldots, \ x\,(t_k)$, where k represents the number of firms that failed during the sample period, and $N \smile K$, is the number of survivors.

Additionally, we also estimate a shared-frailty Cox model, a more general version of the conditional hazard function, that allows us to take in consideration other (unexpected) latent country effects.

$$h_c(t|x(t)) = h_0(t)\, a_c e^{\beta' x(t)} \tag{1.6}$$

$$h_c(t|x(t)) = h_0(t) e^{(\beta' x(t) + v_c)}; \quad v_c = \ln(\alpha_c) \tag{1.7}$$

The estimates of the sensitivity of failure risk to the observable firm-specific, macroeconomic and business environment, energy-related and environment covariates, β, this model enables the estimations of the contribution of the latent macroeconomic factors to the firm's failure risk profile, $\mathbf{v_c}$. Following the same logic than before, a value $\mathbf{v_c} > 1$ indicates that the firms operating in U.S. have higher hazard rates, ceteris paribus. Additionally, a likelihood-ratio test is conducted to test the significance of $\hat{\mathbf{v}}_\mathbf{c}$.

We presented four formulations of the Cox hazard model, these models are called Models I to IV, respectively. These models are progressively less restrictive, they allow for decreasingly fewer similarities between the firms [4].

In addition to the continuous-time Cox models, we also estimate a discrete-time logit specification of the survival model as a main approach. This discrete hazard framework treats the probability of failure within a given time interval as a binary outcome, allowing us to model the log-odds of failure using firm-level covariates. Unlike the Cox model, which relies on proportional hazards and assumes continuous time, the logit specification is more flexible when dealing with grouped or interval-censored data and is particularly useful when the timing of failure events is measured in discrete periods (e.g., annual firm-level observations). The use of both methodologies, Cox and logit, provides a robustness check for our main findings and allows us to validate whether the determinants of failure remain consistent across different statistical frameworks.

[4] Model I represent the conditional hazard function (equation 6) fitted to the pooled energy and non-energy firms that implicitly imposes the restrictions that the sensitivities gathered in β are identical for the different firm-sectors. In addition, an energy-firm dummy variable is included in the model to obtain a conditional estimate of the hazard rate differential between the two firm types (energy and non-energy U.S. firms). Model II represent the conditional hazard function (equation 6) fitted to the pooled energy and non-energy firms adding interaction terms between the control variables and the energy-firm dummy, thus, allowing for the sensitivity of the hazard rate to each variable to differ between the energy-firms and non-energy firms. This means, adding the interaction terms allows us to capture the combined effect of the energy firm status and each indicator variable on the outcome variable (failure/non-failure). The last two models, (III and IV) are fitted to the U.S. energy-firms and non-energy firms separately. Additionally, Model III and Model IV, both depict the fitted conditional hazard function (equation 6) for U.S. energy firms and U.S. non-energy firms, respectively. These two models can be defined as unrestricted in the sense that they allow for more differences between the two firm types compared to Model I and Model II. Such differences are specified in the marginal effect of each covariate to the hazard rate (the sensitivities) and in the baseline hazard function.

Following Shumway (2001) and subsequent extensions, the logit specification is estimated using a panel structure that accounts for time-varying covariates and firm fixed effects, enhancing the comparability with the Cox results.

The estimation of this model is carried out by using the partial maximum likelihood and Efron's (1977) approximation for tied events that refers to firms failing within the same time interval, instead of using inferences based on the Huber-White standard errors that are robust to within-cluster correlations to the failure risk. Furthermore, a class or cluster can be defined by type, such as, energy-firms vs. non-energy firms, or by geographic location.

The variable selection is done through a general specific procedure, we use a forward-and-backward variable (variables can be added or dropped) selection procedure, similar to Lane et al. (1986). Therefore, for each full set of k firm-specific variables, the macroeconomic and business variables, and environmental related variables, we start by comparing the k regressor, and the $\mathbf{k - 1}$ regressor models where one model is retained based on two assumptions: the significance of the covariates are in accordance with the p-values on the individual LR tests, and by using the Akaike information criterion (AIC) we are able to analyse the degrees-of-freedom adjusted explanatory power.

1.3 Data and descriptive statistics

The analysis is based on a comprehensive database that includes both active and inactive publicly listed firms in the U.S. energy sector, as well as firms highly dependent on energy, and non-energy firms. This dataset encompasses both energy users and producers, ensuring a robust sample for our investigation. Covering the period from 2010 to 2022, the dataset comprises a total of 95,743 observations. Our analysis primarily focuses on the financial performance of these firms, examining key metrics such as revenue, common equity, net income, total liabilities, and cash flow, among others. This broad scope allows for a detailed comparison across different sectors and a thorough understanding of the financial dynamics affecting energy and energy-dependent firms.

In addition to examining the financial performance, the analysis also considers various macroeconomic factors specific to the U.S. These factors include the GDP growth rate, inflation rate, foreign exchange rate depreciation, and the Investment Freedom Index, which reflects the level of restrictions on domestic and foreign investments.

Furthermore, the analysis considers two environmental indicators: CO2 intensity and the firms' ESG combined score[5]. CO2 emissions (Kg per PPP $ of GDP) is a measure

[5]The ESG Combined Score is an overall firm score, between 0 to 100, based on the reported

of the carbon intensity of a country's economy. The firms' ESG combined score provides a comprehensive assessment of their environmental, social, and governance performance.

The primary source of accounting data for this analysis is the Compustat-Capital IQ (North America) database, which provides detailed yearly information. The environmental-related data is collected from the Thomson Reuters database. The Compustat-Capital IQ database utilizes various firm characteristics to describe their status. In this research, financially distressed firms are identified as inactive, while non-distressed firms are classified as active[6].

Country-level data used in the analysis are extracted from the World Development Indicators database provided by the World Bank (WDIs-WB).

Additional information on energy U.S. firms can be found in the EIA (U.S. Energy Information Administration (n.d.)) database, and independent statistics and analysis database, that provides up-to-the-hour information on electricity demand across the US electric grid.

We select the energy and non-energy firms based on their sectors identified by the primary Standard Industrial Classification (SIC) code[7]. The second group consists of firms for which the sector's SIC codes are different from the previous ones, and they referred as U.S. non-energy firms. Furthermore, it is important to note that financial firms possess unique characteristics that warrant consideration in survival analysis. As such, we made the decision to exclude them from our dataset to maintain the relevance and accuracy of our findings.

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information in the environmental, social and governance pillars (ESG score) with an ESG controversies overlay. It provides an overall assessment of a company's performance in these areas, indicating its commitment to sustainability, responsible business practises, and ethical conduct. The higher the score the better is the firm performance. Note that ESG combined scores (annual) are not available for every time period between 2010 and 2023. To address this data gap, we use forward fill and/or backward fill methods, applying the most recent available ESG score for each firm in instances where the score is missing for a particular year. Additionally, the same corresponding ESG combined score is attributed to all months within the same year.

[6] To determine the occurrence of firm failures, the default indicator in the Compustat-Capital IQ platform is used. A firm is assigned a value of one if it exits the database, and a value of zero if it remains in the database or exits due to reasons such as mergers and acquisitions.

[7] The energy firms and firms that depend heavily on energy represent the first group, entitled "energy" firms, the SIC code is as follows: 1000 (metal mining), 1040 (gold and silver ores), 1090 (miscellaneous metal ores), 1220 (bituminous coal & lignite mining), 1221 (bituminous coal & lignite surface mining), 1311 (crude petroleum & natural gas), 1381 (drilling oil & gas wells), 1382 (oil & gas field exploration services), 1389 (oil & gas field services), 1400 (mining & quarrying of non-metallic minerals (no fuels)), 2911 (petroleum refining), 2950 (asphalt paving & roofing materials), 2990 (miscellaneous products of petroleum & coal), 4900 (electric, gas & sanitary services), 4911 (electric services), 4922 (natural gas transmission), 4923 (natural gas transmission & distribution), 4924 (natural gas distribution), 4931 (electric & other services combined), 4932 (gas & other services combined), 4941 (water supply), 4950 (sanitary services), 4953 (refuse systems), 4955 (hazardous waste management), 4961 (steam & air-conditioning supply), and 4991 (co-generation services & small power producers).

Including both energy producers and energy users in the analysis is crucial for obtaining a holistic view of the energy sector and its related industries. Producers and users operate under different economic conditions and face distinct sets of risks and opportunities. By incorporating producers, such as companies involved in the extraction and refining of energy resources, and users, such as firms that consume large quantities of energy for manufacturing or operational purposes, we can capture a wide range of sector-specific factors that impact financial performance and survival. Producers are directly affected by fluctuations in energy prices and regulatory changes, while users are influenced by energy costs and efficiency improvements. This dual perspective allows for a more nuanced analysis of how changes in energy markets, economic conditions, and policy environments affect both ends of the supply chain. Ultimately, this comprehensive approach enhances the robustness of the analysis and provides valuable insights into the interplay between energy production, consumption, and financial outcomes. Table A.1 provides a detailed breakdown of our sample in the U.S., categorized according to firms' SIC codes.

[**Table A.1 around here**]

1.3.1 Dependent and independent variables

The dependent variable used in the survival models is the time it takes for a firm to experience failure after its establishment. This is measured in years. The failure indicator is a binary dummy variable that takes the value of one in the year immediately preceding the actual failure and zero otherwise. For all surviving firms, both in the energy and non-energy sectors, this variable takes the value of zero for all years in the sample.

The primary independent variable of interest is a dummy variable that equals one for firms in the energy sector or highly dependent energy sector and zero for non-energy firms. This variable allows us to distinguish between the two sectors in the analysis. Additionally, the column entries of the matrix x_t in equations (5), (6), and (7) (see methodology section) include the energy firm indicator as well as a comprehensive set of control variables.

In this research, we normalized the variables of interest as a key step in data preprocessing. Normalization is particularly important when variables exhibit different scales or units, as is the case with variables such as revenue, net income, and long-term debt, which often span vastly different ranges. By transforming all variables to a standard scale, typically with a mean of 0 and a standard deviation of 1, normalization ensures comparability across variables, facilitating more accurate analysis of their relationships. Furthermore, this process helps to mitigate multicollinearity, improving the robustness and reliability of the statistical models used in the study.

To enhance the accuracy of the model, we employed stratification. This technique is particularly important in survival analysis when certain variables or groups are expected to exhibit distinct baseline hazard functions, even though the relationship with other covariates is assumed to remain consistent across these groups. Stratification effectively addresses heterogeneity in the baseline hazard that cannot be adequately captured using a single shared baseline hazard function. By stratifying, the model separates groups with fundamentally different survival patterns, improving its overall accuracy and reliability. Without stratification, the Cox model assumes a uniform baseline hazard function for the entire dataset, which may lead to inaccuracies if significant differences exist between groups, in this case, energy and non-energy firms. Stratification allows for a more nuanced and realistic modelling of these distinct groups.

The set of control variables includes firm-specific variables, macroeconomic and business variables, and environmental-specific variables. These variables are described in detail in Table A.2. They encompass a range of factors that could potentially influence firm failure and are important to consider in the analysis. The descriptive statistics for the independent variables are provided in Table A.3.

[**Table A.2 and Table A.3 around here**]

1.3.2 Preliminary Data Analysis

As an initial step, we conduct a comparative analysis of the accounting profiles of U.S. energy and non-energy firms, summarized in Table A.4. Columns I to XII report key financial indicators segmented by firm type (energy vs. non-energy) and survival status (survived vs. failed), along with t-tests for mean differences across groups.

The statistics in Columns I and II reveal notable differences between energy and non-energy firms. Energy firms tend to be larger in terms of total assets, equity, net income, capital expenditures, and revenues. However, they exhibit lower average liabilities, adjusted close prices, and liquidity, as indicated by a lower equity-to-assets ratio. Profitability is also weaker among energy firms, with a lower return on assets (ROA) of -3.36% compared to -2.38% for non-energy firms. Although non-energy firms report higher return on equity (ROE), this may reflect greater financial leverage. Furthermore, ESG combined scores are consistently lower for energy firms (19.64 vs. 24.12), suggesting weaker performance across environmental, social, and governance dimensions.

Columns III and IV compare surviving and failed firms, showing that failed firms are substantially smaller and in weaker financial condition. They report significantly lower equity and net income, as well as inferior capital and earnings quality. For instance, failed firms display a lower equity-to-assets ratio (-3.80%) and worse ROA (-2.79%) relative to their surviving counterparts. These patterns hold across both energy and non-energy sectors.

Columns V to VIII further disaggregate the data, confirming that both surviving and failed energy firms differ structurally from non-energy firms along several financial dimensions. Regardless of survival status, energy firms exhibit distinct accounting profiles, reinforcing the argument that failure risk should be modelled separately for energy and non-energy firms.

Overall, the descriptive statistics underscore that surviving firms, regardless of sector, are more financially robust than those that failed. They also confirm that U.S. energy firms differ systematically from non-energy firms, warranting sector-specific modelling approaches in corporate failure prediction.

[**Table A.2 around here**]

1.4 Empirical results

1.4.1 Conditional logit Estimation

This subsection examines the sensitivity of corporate failure risk to firm-specific, macroeconomic, market structure, and environmental factors using a series of conditional logit models. The analysis is based on maximum likelihood estimation, where the dependent variable is a binary failure indicator. Predictor variables include a comprehensive set of controls identified in the literature as relevant to firm performance and survival. A positive coefficient implies that an increase in the corresponding variable is associated with a higher probability of failure, while a negative coefficient suggests a mitigating effect on failure risk.

Model I establishes a baseline by pooling U.S. energy and non-energy firms and sequentially incorporating firm-level (Table A.5), macroeconomic and market structure (Table A.6), and environmental indicators (Table A.7). This model captures the overall relationship between a broad range of covariates and firm survival, without imposing sectoral distinctions.

Model II extends this framework by interacting each covariate with an energy sector dummy variable, allowing the marginal effects of all predictors to vary by firm type.

This enables us to assess whether energy firms respond differently to the same risk factors compared to non-energy firms, thereby capturing sector-specific heterogeneity in failure dynamics.

Models III and IV provide fully disaggregated sector-specific estimates. Model III applies the logit framework exclusively to energy firms, while Model IV focuses solely on non-energy firms. Both models include the full set of covariates, enabling a more granular analysis of the determinants of failure within each sector. Comparing these sector-specific models reveals differences in the drivers of corporate survival across industries, supporting the case for tailored prediction models.

[**Table A.5 to Table A.11 around here**]

In Table A.5, Model I reveals a significant and negative coefficient for the energy dummy variable, indicating a reduced risk of failure for energy firms compared to their non-energy counterparts. This result remains robust even after accounting for various factors such as firm-specific characteristics, macroeconomic indicators, market structure, and environmental variables (Tables A.5-A.8). This finding stands in contrast to the prevailing literature, such as Doumpos et al. (2017), which generally suggests a higher risk of failure for energy firms.

One potential explanation for the negative coefficient observed in Model I could be the inherent stability factors associated with the energy sector. Energy firms often benefit from long-term contracts, regulatory protections, and significant barriers to market entry, which collectively act as a buffer against market fluctuations and economic downturns. These sector-specific advantages may contribute to a lower failure risk compared to other industries. Additionally, energy firms involved in critical services such as electricity and gas supply might receive regulatory advantages or subsidies that help alleviate financial pressures. The stability provided by U.S. government regulations, coupled with the strategic importance of energy supply, could result in reduced failure rates for these firms.

Another possible explanation is the effective management of environmental regulations. Energy firms may have developed more robust strategies to handle environmental challenges, which could contribute to their financial stability. Effective compliance and management of environmental risks might provide an extra layer of protection against failure.

Lastly, the energy sector's economies of scale and operational efficiencies might further explain the lower risk of failure. Large-scale operations and substantial capital investments often lead to improved financial stability, which may be reflected in the reduced risk of failure observed in energy firms compared to non-energy firms.

This discrepancy underscores the necessity of not only examining individual variables but also understanding their interactions to gain a more nuanced perspective on failure risk in the energy sector. It highlights the dynamic nature of risk assessment and the need for a sophisticated approach to capture the complex interplay of factors influencing failure likelihood. These findings offer new insights into the failure dynamics within the energy sector and suggest a need for further investigation into the underlying factors contributing to these outcomes.

Additionally, in Model II (Table A.9), the energy dummy variable is highly statistically significant ($p < 0.0001$). This finding suggests that, in isolation, being an energy firm significantly influences the likelihood of corporate failure compared to non-energy firms.

In Tables A.7, A.8 and A.9, the positive coefficients associated with firm size (as measured by total assets) in Model I, which includes pooled firms, offer intriguing insights into the risk-taking behaviour of larger firms. Specifically, the positive correlation between firm size and risk, as evidenced by the positive coefficients, reflects a notable pattern that aligns with the "too-big-to-fail" hypothesis[8]. This concept suggests that larger firms, due to their significant asset base and substantial market presence, may exhibit a greater propensity for risk-taking. In this context, the positive coefficients indicate that larger firms might leverage their considerable assets and market influence to undertake higher levels of risk, with the expectation that their size and systemic importance will protect them from potential failure.

Additionally, larger firms often have more diversified portfolios and better access to capital markets, which can provide them with a cushion to absorb financial shocks and undertake more aggressive growth strategies. This financial flexibility might lead them to pursue higher-risk investments or expand into new, potentially volatile markets, further amplifying their risk profile.

Moreover, the positive relationship between firm size and risk could also be a function of the scale of operations. Large firms often engage in complex and extensive operational activities that can increase their exposure to various risks, including market volatility, regulatory changes, and operational inefficiencies. These factors collectively contribute to a heightened risk profile for larger firms.

It is also essential to consider that while larger firms might have more resources to manage and mitigate risks, they may also face more significant challenges in maintaining stability due to their size and complexity. This duality of having the means to take on

[8]The "too-big-to-fail" notion posits that large firms benefit from implicit or explicit safety nets, such as government bailouts or regulatory protections, which can embolden them to engage in riskier business practices.

more risk while simultaneously being more vulnerable to the consequences of those risks underscores the complex relationship between firm size and risk.

Similarly, the positive coefficient for assets in Model IV (Table A.11), which is fitted specifically to non-energy firms, indicates that as firms increase in size, they may display a greater propensity to undertake risks. This relationship suggests that larger firms, with their expanded asset base, often perceive themselves as having a buffer of financial resilience or strategic leverage that enables them to engage in riskier ventures that smaller firms might shy away from.

The positive coefficients associated with assets in both Model I (pooled firms) and Model IV (Table A.11) underscore a nuanced connection between firm size and risk-taking behaviour. While the "too-big-to-fail" hypothesis offers a broad explanation, the results highlight the complex dynamics at play. Larger firms might benefit from advantages such as improved access to capital markets, greater diversification, and economies of scale, which collectively enable them to manage and absorb higher levels of risk compared to their smaller counterparts.

Conversely, in Model III, which is specifically fitted to energy firms, the positive relationship between firm size and assets is associated with a decreased risk of corporate failure. This finding contrasts with the trend observed in non-energy firms and suggests that the dynamics of risk-taking in the energy sector might be different. In other words, the risk associated with increased firm size is lower for energy firms compared to non-energy firms.

Energy firms often operate under stringent regulatory frameworks that may provide additional stability. Larger energy firms might benefit more from these regulatory protections, which could mitigate their risk of failure. Energy firms frequently engage in long-term supply contracts and operate in sectors of strategic national importance. This can provide them with a stable revenue stream and reduce their exposure to market fluctuations, contributing to lower failure rates.

Additionally, larger energy firms might achieve significant economies of scale and operational efficiencies that enhance their financial stability. These efficiencies can reduce the cost per unit of production and allow for better risk management. Given the essential nature of energy supply, larger firms in this sector might receive targeted government support or subsidies that further cushion them against financial instability.

In summary, while the positive coefficient for assets in non-energy firms aligns with the "too-big-to-fail" concept, suggesting an increased risk-taking propensity with firm size, the findings in Model III (Table A.10) for energy firms indicate a contrasting relationship where larger size correlates with reduced failure risk. This discrepancy highlights the sector-specific nature of risk management and stability, emphasizing the need for tailored strategies and considerations based on the unique characteristics and regulatory environments of different industries. Further research is needed to explore the underlying reasons for these sector-specific differences and to refine our understanding of how firm size interacts with risk across various contexts.

The coefficients for total equity, net income, and liabilities in Model I (pooled firms, Table A.5 to A.8) exhibit negative signs. This implies that higher values of these financial metrics, including revenue and dividends per share, do not necessarily correlate with an increased probability of failure. Specifically, the negative coefficients suggest that as total equity, net income, and liabilities grow, the likelihood of failure does not necessarily follow suit.

The negative sign associated with the growth of equity implies that an increase in equity contributes to a reduction in the risk of failure for both types of firms. This phenomenon could be attributed to the role of equity as a financial cushion, serving as a safety net that mitigates the risk of insolvency. Shareholders' increased contributions, reflected in higher equity values, act as a protective mechanism for firms.

Both Models III and IV reveal significant distinctions in how balance sheet statement variables affect the risk of corporate failure for energy and non-energy firms. In Model III, which focuses on energy firms, the analysis indicates that increases in equity, net income, liabilities, and dividends per share are associated with a reduced risk of corporate failure. This suggests that for energy firms, stronger financial indicators such as higher equity and net income contribute to enhanced stability and lower failure risk. Additionally, higher liabilities may be seen as indicative of robust growth and investment capacity, which, in the context of energy firms, could be supported by long-term contracts and regulatory advantages that buffer against financial instability.

Conversely, Model IV (Table A.11), which examines non-energy firms, shows that increases in equity, net income, revenue, liabilities, and dividends per share also correspond to a reduced risk of corporate failure. This supports the view that these financial metrics are crucial for financial stability across different sectors.

As total revenue increases, the risk of firm failure decreases for non-energy firms (Model IV), highlighting a positive relationship between revenue and financial stability. However, for energy firms, the significant effect is lower and positive, suggesting that factors other than revenue growth might dominate in influencing the failure risk for these firms. This disparity underscores the importance of industry-specific considerations in evaluating the impact of financial variables on failure risk.

The negative sensitivity of failure risk to net income in both Models III and IV implies that an augmentation in net income corresponds to a diminished likelihood of failure for both energy and non-energy firms. This consistent negative relationship underscores the robustness of net income as an indicative measure of financial health spanning diverse sectors. The findings suggest that, irrespective of industry nuances, an increase in net income is generally associated with improved financial stability and resilience for companies. This aligns with the conventional understanding that higher net income reflects enhanced profitability, providing firms with greater resources to navigate challenges and mitigate the risk of failure.

In our analysis, capital expenditure emerges as a crucial indicator for energy firms. Model III reveals that elevated levels of capital expenditure correlate with increasing corporate failure risk within the energy sector. Moreover, the typically higher leverage observed in energy firms introduces another dimension to their failure risk profile (Table A.10). Specifically, our findings indicate that increased long-term debt exacerbates the risk of failure among energy firms. Conversely, these coefficients appear to exhibit less significant impact on non-energy firms (Table A.11), suggesting a sector-specific dynamic in the relationship between capital expenditure, long-term debt, and corporate failure risk.

Interestingly, the majority of the firm financial ratios analysed do not exhibit statistical significance, with the exception of the dividend per share indicator variable (Model I, Model III and Model IV). Remarkably, a higher level of dividends per share is associated with a decreased failure risk for both U.S. energy firms and non-energy firms, as enumerated before. This finding suggests that firms distributing higher dividends per share demonstrate a level of financial stability that contributes to a lower likelihood of failure.

Apart from the lack of statistical significance, another interesting observation is that higher capitalization levels (equity/assets) decrease the failure risk for non-energy firms but insignificant for energy firms (Table A.10 and Table A.11). This finding can be attributed to the connection between leverage and profitability. The exact leverage of a firm is influenced by a combination of internal and external factors, which may vary across different types of firms. Notably, U.S. energy firms tend to operate with higher leverage compared to non-energy firms. This distinction in leverage levels could contribute to the varying effects on failure risk observed between the two types of firms. Energy firms in the oil and gas sector often require substantial upfront capital investments for exploring and producing energy resources. According to Kim et al. (2019), oil projects are inherently risky and demand higher capital outlay. Consequently, this capital requirement leads to higher debt for energy firms. In the literature, one common financing approach for large projects is project finance (Pierru et al., 2013), and such projects tend to be highly leveraged compared to non-project financed ventures (Shah et al., 1987). In contrast, non-energy firms, depending on their business model and industry, may have different risk profiles and capital requirements. Thus, the marginal gain from leveraging would likely be higher for energy firms than for non-energy firms, as it allows the former to allocate more funds to their investments.

A notable similarity between energy firms and non-energy firms is observed in the directional impact of oil price fluctuations on their financial stability. In Model III (Table A.10), which examines energy firms, oil price shocks show a statistically significant and pronounced effect on cash flow and liquidity. Specifically, sharp declines in oil prices reduce revenues for energy firms, leading to increased financial stress, higher refinancing costs, and a deterioration in credit ratings. These effects collectively heighten the risk of corporate failure. The positive relationship between oil price stability and financial health aligns with previous findings, such as those by Korotin, Ulchenkov, and Islamov (2017), which highlight the substantial dependence of energy firms on oil revenues and their vulnerability to commodity price volatility.

Interestingly, oil price fluctuations exhibit similar directional effects for non-energy firms, as reflected in Model IV. While non-energy firms are less directly reliant on oil revenues, changes in oil prices significantly affect their operational costs and overall financial performance. Rising oil prices, for instance, lead to higher production and transportation costs, which compress profit margins, while falling oil prices may signal broader economic slowdowns that reduce consumer demand. Despite these distinct channels, the consistent signs of the impact, negative effects during price declines or increases in volatility, highlight the pervasive influence of oil prices across sectors.

This alignment in the directional impact of oil prices underscores the widespread importance of commodity price management. For energy firms, mitigating oil price volatility remains critical, given the direct revenue dependency. Non-energy firms, on the other hand, must focus on managing indirect effects, such as cost pressures and demand shifts, to sustain financial stability. These insights reveal that while the magnitude and channels of influence differ, the fundamental risks posed by oil price fluctuations are shared across industries. This commonality points to the broader significance of robust risk management strategies and the need for sector-specific adaptations to navigate commodity price uncertainty effectively.

Our analysis reveals that an increase in the global spot price of uranium is associated with a heightened risk of corporate failure for both energy firms (Model III) and non-energy firms (Model IV). This outcome is consistent with expectations, given the critical role uranium plays as a primary fuel source for nuclear power generation. For energy firms, particularly those involved in nuclear power, rising uranium prices can significantly impact profitability. This is because the increased cost of uranium, a vital input for their operations, may not be easily passed on to consumers due to regulated pricing structures or long-term supply contracts. Consequently, the higher operational costs associated with elevated uranium prices can strain the financial stability of these firms.

Furthermore, the broader impact of rising uranium prices extends beyond energy firms to affect non-energy firms as well, as they may experience indirect effects through increased energy costs or economic uncertainty. This dynamic underscores the economic vulnerability associated with fluctuations in key input prices and highlights the potential challenges for industries reliant on stable energy costs. The observed escalation in corporate failure risk in response to rising uranium prices suggests that for nuclear energy firms in the U.S., the increasing volatility of uranium costs could threaten the economic viability of nuclear power investments. This situation raises concerns about the sustainability of investing in nuclear energy in the face of volatile and potentially escalating input costs.

For energy firms, long-term debt appears to play a crucial role in influencing corporate performance and financial stability. As indicated in Table A.10 (Model III), higher levels of long-term debt are associated with an increased risk of corporate failure for energy firms. This result can be related to energy firms often operate in capital-intensive sectors with fluctuating revenue streams. High levels of long-term debt increase the burden of debt servicing costs, which can strain financial resources, particularly during periods of low commodity prices or economic downturns. This financial strain can heighten the risk of default and corporate failure.

Energy firms are highly sensitive to fluctuations in commodity prices, such as oil, as proven by the sensitivity of failure risk to oil prices. When these prices drop, revenue decreases, making it more challenging for firms to meet their debt obligations. Consequently, higher long-term debt exacerbates the financial instability during adverse market conditions.

Additionally, high leverage, as reflected by increased long-term debt, amplifies financial risk. In volatile markets, the additional financial pressure from debt payments can lead to reduced operational flexibility and increased vulnerability to financial distress.

Conversely, for non-energy firms, as shown in Model IV (Table A.11), higher long-term debt appears to be associated with a decreased risk of corporate failure and the impact is not significant. This counter-intuitive result may be explained by several factors, such as non-energy firms often operate in sectors with more diversified revenue streams, which can provide a buffer against the financial strain of long-term debt. This diversification allows these firms to manage debt more effectively and maintain financial stability. Non-energy firms may benefit from lower borrowing costs due to their strong credit ratings or more favourable market conditions. Lower cost of capital can reduce the financial burden associated with long-term debt, thereby mitigating its risk.

The differing impacts of long-term debt on corporate performance in energy versus non-energy firms highlight the sector-specific dynamics that influence financial risk. For energy firms, high levels of long-term debt can amplify vulnerability to market fluctuations and economic downturns, while non-energy firms may benefit from more stable financial conditions that mitigate the risks associated with debt. Understanding these sector-specific implications is crucial for developing effective financial strategies and risk management practices tailored to the unique characteristics of each industry.

Interestingly, the expansion of the Environmental, Social, and Governance (ESG) combined score emerges as a statistically significant factor in reducing the failure risk for both U.S. energy firms and non-energy firms across all models (Model I, II, III and Model IV). This intriguing finding underscores the potential risk mitigation associated with a higher ESG combined score, indicating that firms prioritizing environmental, social, and governance considerations demonstrate a lower likelihood of failure. This result suggests a positive connection between strong ESG performance and overall financial resilience, emphasizing the importance of sustainable and socially responsible business practices in enhancing firm stability across diverse sectors. In Model II (Table A.9) the positive sign associated with the interaction between energy dummy and ESG combined score indicates that a higher ESG score is associated with a reduced risk of failure for energy firms. This suggests that energy firms with better ESG practices are more resilient.

Moreover, the analysis reveals that the ESG combined score appears to have a more pronounced impact on reducing failure risk for non-energy firms (Model IV - Table A.11) compared to their energy counterparts (Model III - Table A.10). This differential impact may be attributed to several factors. Non-energy sectors may face different ESG-related pressures and opportunities compared to the energy sector. For example, non-energy firms might be more directly affected by consumer preferences and regulatory requirements related to sustainability, making ESG performance a more critical determinant of financial stability in these industries. Non-energy firms may operate in sectors where regulatory frameworks and market expectations around ESG performance are more stringent. Enhanced ESG practices can lead to better compliance, lower legal risks, and improved market perception, which can significantly reduce the risk of failure.

Overall, the finding underscores the importance of integrating ESG considerations into corporate strategies as a means of enhancing stability and reducing failure risk. The differential impact on energy versus non-energy firms highlights the varying significance of ESG performance across sectors, suggesting that while strong ESG practices are beneficial for all firms, the extent of their impact may vary depending on industry-specific factors and stakeholder expectations.

Next, we examine the sensitivity of failure risk to macroeconomic and market structure variables, as detailed in Table A.10 (Model III) for energy firms and Table A.11 (Model IV) for non-energy firms. The relationship between real GDP growth and failure risk reveals consistent patterns across both sectors. For energy and non-energy firms alike, an increase in real GDP growth is significantly associated with a reduced likelihood of corporate failure. This finding aligns with existing literature, such as Altman et al. (2005), which underscores the stabilizing effect of economic expansion on firms.

For non-energy firms, the reduction in failure risk can be attributed to improved market conditions, higher consumer demand, and more accessible financing during periods of economic growth. These factors enhance revenue streams, strengthen liquidity positions, and provide firms with greater resilience against financial shocks. Similarly, energy firms benefit from increased industrial activity and energy consumption, which bolster demand for their products and services during economic upturns.

The shared sensitivity to real GDP growth highlights the broad influence of macroeconomic conditions on firm stability, regardless of sector. However, the channels through which these effects manifest differ slightly between energy and non-energy firms. Non-energy firms primarily gain through expanded market opportunities and cost efficiencies, while energy firms benefit from higher energy demand and stronger commodity prices. These findings emphasize the critical role of macroeconomic stability in fostering a supportive environment for corporate success across diverse industries.

Additionally, energy firms are often more exposed to fluctuations in global oil, and other commodity prices, as supported by the previous results, which may have a more pronounced effect on their financial stability than domestic economic growth alone. During periods of economic expansion, the positive effects of GDP growth might be counterbalanced by volatile commodity prices, which can impact energy firms' profitability and risk profile. Energy firms may have significant capital expenditure requirements and financing constraints that are less sensitive to short-term GDP growth fluctuations. While a growing economy generally benefits firms, energy firms might face unique challenges related to their investment cycles and U.S. regulatory environments that dampen the impact of GDP growth on their failure risk.

Inflation appears to increase the risk of corporate failure across the pooled firms, as evidenced by the results from Tables 6 through 8. Inflation poses a significant challenge for many sectors, but its impact is particularly pronounced for non-energy firms. In terms of Model II (Table A.8) the positive coefficient (0.1295, $p = 0.0000$) signifies that higher inflation increases the risk of failure. This effect is consistent across both energy and non-energy firms.

As shown in Table A.10, energy firms exhibit significant vulnerability to inflationary pressures. This can be attributed to their substantial input costs tied to raw materials and energy resources, which are highly sensitive to inflation. Rising prices for inputs such as oil, gas, and other commodities directly erode profit margins, intensifying financial instability and increasing the likelihood of corporate failure. Moreover, the capital-intensive nature of the energy sector amplifies these challenges. Energy firms typically operate with high fixed costs and substantial debt obligations, making them particularly exposed to inflation-induced interest rate hikes. Such increases in borrowing costs further strain their financial positions by reducing cash flow and limiting their ability to meet financial obligations, thereby elevating the risk of failure.

Table A.11 indicates that non-energy (Model IV) firms demonstrate a stronger sensitivity to inflation in terms of failure risk. For these firms, inflation can adversely impact production costs, reduce consumer purchasing power, and disrupt supply chains, all of which contribute to financial pressures. Additionally, higher inflation may limit the ability of non-energy firms to pass on cost increases to customers, squeezing profit margins and exacerbating financial vulnerability.

The heightened sensitivity of energy firms to inflation (Table A.10) reflects their unique cost structures, reliance on volatile commodity markets, and exposure to macroeconomic fluctuations. On the other hand, the observed vulnerability of non-energy firms to inflation underscores broader challenges faced across industries, including reduced consumer spending and supply chain disruptions. These findings highlight the importance of inflation-specific risk management strategies tailored to the distinct operational and financial characteristics of each sector.

Additionally, the Investment Freedom Index (IFI), which evaluates the ease of investment and the regulatory barriers within a country, demonstrates similar impacts on corporate failure risk across different firm types. In both Model III (Table A.10) and Model IV (Table A.11), an increase in the IFI is associated with a higher risk of corporate failure for both energy and non-energy firms. This counter-intuitive finding suggests that while greater investment freedom typically fosters economic growth and innovation, it may also introduce heightened competition and market volatility. For energy firms, the increased failure risk might stem from the sector's heavy reliance on capital-intensive projects and the susceptibility of such investments to policy changes and market fluctuations. Similarly, for non-energy firms, greater investment freedom could lead to intensified competitive pressures, potentially destabilizing less efficient or highly leveraged firms. These results underline the complex interplay between investment freedom, sector-specific characteristics, and corporate stability, emphasizing the need for nuanced regulatory frameworks tailored to mitigate the risks associated with increased investment flexibility.

In the context of market structure, the analysis reveals an intriguing trend for both energy and non-energy firms as shown in Table A.10 and Table A.11. Specifically, an increase in sector concentration, as measured by the Herfindahl-Hirschman Index (HHI), is associated with a decrease in the risk of corporate failure. This relationship prompts a closer examination of several underlying economic factors.

In more concentrated markets, where a few firms hold significant market shares, there is often less competitive pressure, which can lead to greater financial stability for firms within these sectors. Higher concentration can result in more stable pricing power and better control over market conditions, which might contribute to lower failure risks. This stability arises because firms in concentrated markets may benefit from economies of scale, have stronger negotiating positions with suppliers and customers, and face reduced competitive threats.

Likewise, increased sector concentration may also facilitate easier access to financing and investment, as lenders and investors may perceive these firms as less risky due to their dominant market positions. Additionally, in a concentrated market, firms might have better opportunities to leverage strategic partnerships and long-term contracts, further enhancing their financial stability.

Nevertheless, it is also important to consider that while increased concentration might provide certain advantages, it could also lead to regulatory scrutiny and potential anti-competitive concerns. The benefits of market concentration are context-dependent and can vary based on the specific dynamics of the industry and the regulatory environment.

However, when examining the total energy market share variable (Table A.10 and Table A.11), we observe that it is associated with an increased risk of corporate failure for energy and non-energy firms. This finding suggests that a higher market share in the energy sector might correlate with greater financial vulnerability rather than stability. Several potential explanations could account for this relationship. Additionally, this result is supported by Model II (Table A.8). The positive coefficient in Table A.10

(0.5227, p = 0.0001) suggests that a larger share of the energy market is associated with a higher risk of failure for energy firms. This might reflect competitive pressures or market saturation effects specific to the energy sector.

Firstly, energy firms with larger market shares may face higher operational and financial risks due to their scale. Large market share can often lead to increased exposure to market fluctuations, regulatory changes, and competitive pressures. For instance, dominant firms may have significant exposure to volatile commodity prices and geopolitical risks that can amplify their financial instability.

Additionally, larger firms might experience dis-economies of scale where the costs associated with managing extensive operations outweigh the benefits of their size. This could result in operational inefficiencies and higher financial risk. Furthermore, dominant firms could face heightened public and investor scrutiny, which might increase the perceived risk of failure, especially if they are involved in controversial or high-risk activities.

In contrast to the stability typically associated with market concentration, this result highlights that in the context of the energy sector, having a larger market share does not necessarily translate into lower risk. Instead, it may expose firms to additional risks that can contribute to a higher probability of failure.

Finally, the environmental indicator, CO2 emissions in U.S. (measured in kilograms per purchasing power parity (PPP) dollar of GDP), emerges as statistically significant in all Models (Model I-IV). This distinctive pattern suggests that the CO2 emissions indicator bears significance for both energy and non-energy firms. The discernible result suggests that, in this model, an escalation in CO2 emissions is associated with an increase in the corporate failure risk.

This finding underscores the notion that, for firms, environmental sustainability practices, as reflected in CO2 emissions, play a substantive role in influencing their financial resilience. The observed relationship may be attributed to shifting consumer preferences, evolving regulatory landscapes, or heightened societal expectations regarding corporate responsibility. Firms, particularly those contributing more significantly to CO2 emissions per unit of economic output, may face increased risks stemming from potential regulatory penalties, shifts in consumer sentiment, or operational disruptions.

Overall, understanding the dynamics of these financial variables, macroeconomic and business variables, and environmental indicators, and their impact on failure risk is essential for refining risk assessment models and informing strategic decision-making for both policymakers and investors. It underscores the importance of considering industry-specific nuances in interpreting the relationships between financial metrics and the likelihood of failure. The interaction terms in Model II (Table A.9) reveal nuanced differences in how various factors impact the failure risk of energy versus non-energy firms. While some factors, like firm size and liabilities, exhibit sector-specific effects, others, such as ESG scores, uniformly contribute to reduced failure risk. Again, this analysis underscores the importance of sector-specific dynamics in evaluating corporate failure risks and highlights the varying impacts of financial and macroeconomic variables across different industries.

In evaluating the goodness-of-fit measures, we observe that the McFadden pseudo-R^2 statistics presented in Tables A.5 through A.11 are remarkably similar across models incorporating firm-specific and U.S. macroeconomic variables, as well as those using solely firm-specific variables. This similarity suggests that firm-specific accounting metrics are integral to accurately predicting corporate failure, indicating their fundamental role in the model's performance.

Additionally, the inclusion of macroeconomic factors in the logit models enhances their explanatory power for both energy and non-energy firms. This is evidenced by the notable percentage increase in log-likelihood values and the corresponding decrease in Akaike Information Criterion (AIC) values, which collectively signify a better model fit and improved predictive accuracy when macroeconomic variables are included.

However, the introduction of market structure variables into the pooled model (Model I), as shown in Table A.7, results in an increased AIC value. This suggests a deterioration in the model's fit compared to models that do not include these predictors. The increased AIC indicates that, despite adding market structure variables, the model becomes less efficient in capturing the underlying patterns in the data, possibly due to over-fitting or the additional complexity not being justified by improvements in predictive performance.

Lastly, we perform the confusion matrix for all the previous logistic regressions to evaluate the model's performance in classifying binary outcomes (failure or not failure). The confusion matrix allows us to calculate metrics such as accuracy, recall (sensitivity), specificity, and F1-score. Generally, the model that includes macroeconomic indicators has higher accuracy and precision (Table A.6). In terms of sensitivity, which measures the proportion of true positive predictions out of all actual positive cases, it is notably high for all the models.

To ensure the robustness and validity of our empirical framework, we conduct a series of diagnostic and sensitivity analyses addressing key model assumptions. For the Cox proportional hazards model, we test the proportional hazards assumption using Schoenfeld residuals and graphical inspections of scaled residuals over time. The results indicate no systematic violations of proportionality for the main covariates. In addition, we assess potential misspecification by examining alternative functional forms, including transformations of key variables and the inclusion of interaction terms. For the discrete-time logit specification, we evaluate the assumption of independence across observations by accounting for the panel structure of the data and clustering standard errors at the firm level. We also test the sensitivity of our results to alternative model specifications, including different sets of covariates, lag structures, and sub-sample analyses. Across these variations, the main findings remain qualitatively unchanged, supporting the robustness of our conclusions and confirming that the observed relationships are not driven by specific modelling choices.

1.5 Robustness

1.5.1 Conditional Survival Estimation

In this subsection, we present an approach using the Cox proportional Hazard model, focusing specifically on failure-risk sensitivity to factors such as firm characteristics, macroeconomic and market structure indicators, and environmental variables. To conduct our analysis, we employed survival analysis and initiated by computing the actual time to failure.

To begin with, we created a new variable to represent the survival time for each firm. This variable was calculated as the time difference between the occurrence of the event (failure) and the start of the observation period. Figure A.2 illustrates the histogram for both energy and non-energy U.S. firms that experienced failure during the designated period. The histogram demonstrates a left-skewed distribution, indicating that the tail extends towards the left side. This implies that there are less observations with shorter survival duration's, meaning failures do not tend to happen relatively quickly, and more observations with longer survival duration's, indicating that failures take longer time to occur. In other words, firms, on average, tend to experience failures later rather than earlier.

Understanding this left-skewed nature of the histogram (Figure A.2) is vital for risk assessment, making informed business decisions, and gaining insights into the expected lifespan of firms in both the energy and non-energy sectors. This information can be crucial for stakeholders in these industries. Moreover, Figure A.3 and Figure A.4 depict histograms for U.S. energy and non-energy firms, respectively, that also experienced failure during the specified period. Similar to Figure A.2, these histograms also exhibit a left-skewed pattern. However, in Figure A.3, which illustrates the failure distribution among energy firms, despite the left-skewed pattern, notable distinctions emerge in the failure profiles between energy and non-energy firms. Specifically, it reveals a higher incidence of failures among energy firms during earlier time periods within the specified duration.

[Figure A.2-A.4 around here]

Secondly, we employed the Kaplan-Meier survival analysis to examine the survival curves for the entire sample of U.S. firms, including both energy and non-energy sectors, as well as for each sector individually. This analysis was conducted using a straightforward model that does not account for covariates. The resulting Kaplan-Meier curves, which illustrate the cumulative survival probabilities over time, are presented in Figures A.5 through A.8.

[Figure A.5-A.8 around here]

As shown in Figure A.5, the Kaplan-Meier survival curve begins at 1.0 (100%) at time 0, representing the start of the observation period in 2010, when all pooled firms are initially considered as surviving. Over time, the survival probability progressively declines, reflecting a decrease in the proportion of firms that remain operational. This curve effectively illustrates the probability that a firm will "survive" up to a given point in time. As more firms fail over the observation period, the survival probability diminishes, approaching zero toward the later stages of the dataset.

Figures A.6 and A.7 present Kaplan-Meier survival curves for U.S. energy and non-energy firms, respectively. These curves, like the pooled data in Figure A.5, show a declining survival probability over time. As time progresses, more firms encounter failure events, causing the survival probability to decrease. The Kaplan-Meier estimator dynamically adjusts the survival probability based on the number of observed failures and the remaining firms under observation, whether censored or surviving. These figures highlight the survival dynamics within the specific subgroups of energy and non-energy firms.

Additionally, figure A.8 illustrates the Kaplan-Meier survival curves for both energy and non-energy firms in the U.S., depicting their cumulative survival probabilities over time. At the outset of the observation period, both energy (blue line) and non-energy (red line) firms start with a survival probability of 1.0, reflecting that all firms are initially surviving. Throughout the observation period, both survival curves demonstrate a similar downward trend, indicating a gradual reduction in survival probability as time progresses. Initially, the survival curves for energy and non-energy firms are closely aligned, particularly in the early to mid-stages of the period (up to approximately

3000 days). However, after this point, the curves begin to diverge slightly, with energy firms maintaining a marginally higher survival probability compared to non-energy firms, supporting the previous results from the logit analysis. Overall, the data reveal a consistent decline in survival probability for both firm types, highlighting that the risk of failure steadily increases as time extends.

Thirdly, this subsection investigates the sensitivity of failure risk to various factors, including firm-specific characteristics, macroeconomic conditions, market structure, and environmental indicators. The results for the Cox proportional hazards model applied to the pooled sample of firms (Model I) are detailed in Tables A.12 through A.15. These tables present the model's performance across different sets of variables. Furthermore, in Model II (Table A.16), we introduced the interaction term *energy dummy* to assess the differential impact of these variables on energy versus non-energy firms. The results, presented in Table A.16, illustrate how this interaction term influences the relationship between failure risk and the control variables.

Lastly, we examined the unrestricted models, which apply the Cox proportional hazards model separately to energy firms (Model III) and non-energy firms (Model IV). These results are detailed in Tables A.17 and A.18, respectively. For each of these models, we analysed how firm specific information, macroeconomic factors, market structure, and environmental indicators affect failure risk. Hazard rates, represented by the exponentiated coefficients (Exp(coef.)), are reported for each model to provide insights into the relative risk of corporate failure associated with these variables.

[**Table A.12-A.18 around here**]

The incorporation of explanatory variables and their interactions (Model II -Table A.16) with the energy firm binary variable provides compelling evidence that energy firms possess a distinct failure profile compared to non-energy firms. This corroborates and extends the earlier findings from the logit regression, shedding light on the nuanced dynamics influencing failure risks within the energy sector. While the direct effect of the energy dummy is not statistically significant, the interaction terms provide valuable insights into how specific factors, like assets and net income, impact failure risk differently across these sectors. The results underscore the complexity of modelling failure risk and suggest that further exploration may be needed to fully understand the risk profiles of energy versus non-energy firms.

The positive coefficients associated with firm size (as shown in Tables A.12 to A.18) underscore that larger firms may be more prone to taking on additional risks, potentially under the assumption that they are "too big to fail", as indicated by the logit regression results. This tendency reflects the significant and systemic role that large firms play in the U.S. economy.

Contrary to the logit regression findings, the net income variable consistently exhibits a positive sign in models Model I (Table A.12 to Table A.15), II (Table A.16), and IV (Table A.18). This discrepancy suggests that while net income might portray positive financial performance, firms, especially non-energy firms, could be concurrently burdened with significant debt to fuel their growth. In line with the findings yielded by the logit regression analysis, an increase in net income appears to correlate with a reduced risk of corporate failure for energy firms (Model III), as supported by Model II. The divergence in results emphasizes the importance of industry-specific variables and the intricate interactions among financial metrics in shaping the risk landscape. Such nuances underscore the necessity for a comprehensive understanding of sector-specific dynamics in assessing failure risk.

Moreover, our analysis consistently indicates that capital expenditure is associated with a decrease in corporate failure risk across all models (Models I, II, III, IV). Notably, this indicator holds particular significance for energy firms, largely attributed to their characteristic high levels of capitalization. Energy firms typically exhibit elevated capitalization levels due to the substantial upfront investments required for exploration, production, and infrastructure development. These investments are necessary for the extraction, refinement, and distribution of energy resources such as oil, gas, and renewable sources. Additionally, the capital-intensive nature of energy projects, which often involve long-term commitments and large-scale infrastructure, contributes to the high capitalization levels observed in the industry. Consequently, the substantial capital investment acts as a protective buffer, mitigating the risk of corporate failure by supporting operational resilience and long-term sustainability.

Additionally, our analysis indicates a positive correlation between long-term debt and the risk of corporate failure among energy firms, as evidenced by Model III (Table A.17), which corroborates the findings from the logit analysis. Energy firms typically exhibit high leverage due to the extensive capital requirements associated with exploration, development, and infrastructure projects. To finance investments in resource extraction, refining facilities, and distribution networks, these firms often rely heavily on long-term debt. This dependence on debt financing makes energy firms particularly vulnerable to fluctuations in interest rates, market conditions, and regulatory changes. Consequently, the impact of long-term debt on the failure risk of energy firms is significantly heightened, reflecting their increased sensitivity to financial and economic pressures.

An examination of the revenue indicator reveals that, for non-energy firms, an increase in revenue is associated with a higher risk of firm failure, as shown in Model IV

(Table A.18). This finding suggests that revenue growth, in the context of non-energy firms, might be linked to aggressive expansion or overextension, which can increase failure risk. Conversely, no significant effect of revenue growth on failure risk is observed for energy firms. This discrepancy can be attributed to the unique financing practices prevalent in the energy sector. In energy firms, revenue growth may not necessarily indicate financial stability or increased risk in the same way it does for non-energy firms. Energy firms often rely heavily on long-term capital investments and debt financing rather than equity, which may insulate them from the typical risks associated with revenue fluctuations. Additionally, the capital-intensive nature of the energy sector often involves substantial upfront investments with long-term revenue generation models, which could mitigate the immediate impact of revenue changes on failure risk.

In summary, the diverse relationships observed across different variables and models underscore the importance of delving into industry-specific factors and financing practices to gain a nuanced understanding of failure risk for both energy and non-energy firms. These complexities challenge the application of a one-size-fits-all approach and emphasize the need for tailored risk assessment models that account for industry intricacies.

Tables A.12 through A.18 illuminate substantial disparities in the sensitivities of failure risk to financial ratio indicators between energy and non-energy firms. The presence of statistically significant differences in the majority of estimated sensitivities underscores that the failure risk profiles of these two firm types diverge significantly. The growth of Return on Equity (ROE) and the Dividend per Share (Div/share) ratio appear to reduce the risk of corporate failure for non-energy firms (Model IV). This suggests that the financial health of non-energy firms benefits from a stronger equity base, potentially acting as a buffer against failure. In contrast, the lack of significance for energy firms (Model III) may imply that other factors or financial structures play a more prominent role in influencing their failure risk. Additionally, this finding suggests that higher profitability and satisfactory shareholder dividends have a positive impact on the financial stability of non-energy firms, contributing to a lower risk of failure. In contrast, the Dividend per Share (Div/share) ratio exhibits no significant effect on the failure risk of U.S. energy firms (Table A.17), a departure from the results obtained in the logit regression analysis. This inconsistency underscores the nuanced nature of the relationship between dividend distribution and failure risk within the energy sector.

The observed distinctions in the impact of financial ratios on failure risk highlight the need for tailored risk management strategies, acknowledging the unique characteristics and financial structures prevalent in the energy and non-energy sectors. The positive influence of ROE growth, and dividend distribution on failure risk for non-energy firms suggests that a focus on profitability and sound financial practices can contribute to resilience. However, the lack of similar effects for energy firms indicates that alternative considerations, such as industry-specific risk factors or financing practices, may be at play.

Interestingly, a consistent and statistically significant finding emerges across all models (Model I to IV). The ESG combined Score demonstrates a consistent pattern of decreasing the risk of corporate failure for both energy (Table A.17) and non-energy U.S. firms (Table A.18). This reaffirms and strengthens the findings documented in prior literature, emphasizing the pivotal role of incorporating environmental indicators into corporate failure prediction analysis (Pätäri et al. (2014); Arslan-Ayaydin and Thewissen (2016); Doumpos et al. (2017); Christmann, 2000; and Delmas, 2001). Notably, the impact of the ESG combined Score appears more pronounced for non-energy firms (Table A.18) compared to their energy counterparts (Table A.17).

This outcome suggests that environmental, social, and governance factors exert a more substantial influence in mitigating the risk of corporate failure for non-energy firms. It underscores the critical importance of incorporating sustainability practices and responsible business management into the operational framework of non-energy firms. The consistent and notable result across all models underscores the positive influence of the ESG combined Score in reducing the risk of corporate failure for both energy and non-energy firms. The relatively stronger effect observed in the case of non-energy firms reinforces the notion that a robust commitment to ESG principles is particularly impactful in enhancing the financial resilience of non-energy firms. This finding resonates with the growing recognition of the business value associated with sustainable and socially responsible practices, emphasizing their role not only in risk mitigation but also in fostering long-term corporate viability.

Next, we examine the sensitivity of corporate failure risk to macroeconomic and market structure variables through the lens of the generalized Cox proportional hazards model. The results, detailed in Tables A.13 through A.18, reveal a significant inverse relationship between real GDP growth and corporate failure risk. Specifically, an increase in real GDP is consistently associated with a reduced risk of corporate failure for both energy and non-energy firms, as shown in Tables A.17 and 18. This finding aligns closely with the earlier results from the logit survival model, reinforcing the robustness of this relationship across methodological approaches. The observed effect can be attributed to the positive impact of economic expansion, which fosters improved market conditions, bolsters consumer demand, and enhances access to financing. These factors collectively contribute to greater financial stability and resilience, mitigating the likelihood of corporate distress. The consistency of these findings across models underscores the critical role of macroeconomic stability in shaping firm-level outcomes and highlights the importance of incorporating economic growth considerations into corporate risk management and policy frameworks.

Furthermore, as observed in the logit analysis, inflation emerges as a significant concern for non-energy firms, while it appears to have a negligible direct impact on energy firms in the Cox model results. This finding contrasts with the outcomes of the logit survival model, where inflation significantly influenced the failure risk of energy firms. The heightened sensitivity of energy firms to inflationary pressures, as suggested in prior literature (Smolarski and Vega (2013)), can be attributed to the inherent volatility of energy commodities, particularly oil and natural gas prices. Inflation-driven increases in energy prices elevate input costs for energy firms, eroding profit margins and intensifying financial stress. This nuanced disparity between the two modelling approaches highlights the complex interplay between macroeconomic factors, such as inflation, and the operational vulnerabilities of energy firms, which may exacerbate their risk of failure under certain economic conditions.

Turning to market structure, an increase in market share for energy firms is consistently associated with a heightened risk of corporate failure across all models, except Model III, which exclusively examines energy firms. This result further underscores the elevated vulnerability of energy firms to corporate failure. Notably, this heightened risk raises important concerns about potential spillover effects, where corporate failures within the energy sector could propagate instability to other sectors. Such inter-dependencies emphasize the critical need for robust risk management strategies within the energy sector to mitigate broader economic repercussions and safeguard overall market stability.

In the final analysis, particular focus is placed on the CO2 emissions indicator, revealing its remarkable predictive power for both U.S. energy and non-energy firms, as evidenced in Model III (Table A.18) and Model IV (Table A.17). Notably, we observe a consistent positive association between the CO2 emissions indicator and the risk of failure across both sectors. This robust relationship underscores the significant impact of environmental regulations and sustainability concerns on corporate failure risk. In the context of the U.S., stringent environmental regulations aimed at curbing greenhouse gas emissions impose substantial compliance costs on firms, particularly those in energy-intensive industries. Energy firms, in particular, face heightened scrutiny and financial liabilities related to their carbon footprint, as they navigate evolving regulatory landscapes and societal expectations for environmental responsibility. Consequently, the predictive power of CO2 emissions in increasing the risk of corporate failure underscores the critical importance of environmental factors in shaping the operational and financial viability of firms across diverse sectors.

This nuanced finding highlights the importance of a holistic approach to corporate failure prediction, acknowledging the multifaceted nature of risk factors and their varying degrees of influence across different industries Doumpos et al. (2017). While environmental indicators are crucial considerations in assessing a firm's overall sustainability, underscoring the need for a comprehensive understanding of the interplay between environmental, financial, and operational factors in determining the resilience of both energy and non-energy firms in the face of potential failure.

One contributing factor to this may be the increasing implementation of stringent regulations and policies in the U.S., aimed at reducing greenhouse gas emissions and addressing climate change. In particular, non-energy firms, especially those with substantial CO2 emissions, may face elevated compliance costs and penalties for failing to meet emission reduction targets. As a result, their financial performance may be adversely affected, leading to an increased risk of failure.

The heightened emphasis on environmental responsibility and the adoption of sustainable practices places non-energy firms under greater scrutiny. Consequently, it becomes imperative for them to adapt swiftly and align their operations with evolving environmental standards to mitigate the financial and failure risk associated with CO2 emissions.

Regarding the goodness-of-fit measures, we observe that the McFadden pseudo-R^2 statistics reported in Tables A.12 through A.18 are very similar for the models based on firm-specific and country-specific variables. This close resemblance suggests that the accounting statement variables carry most of the predictive power. Notably, the inclusion of U.S. macroeconomic and market structure variables into the survival model enhances the model's predictive power for both firm types, indicating that both energy and non-energy firms are sensitive to the economic environment and market structure. Furthermore, the addition of environmental indicators further boosts the predictive power for both types of firms. However, non-energy firms demonstrate a higher sensitivity to these environmental indicators compared to energy firms. This finding is also supported by the percentage decrease in the AIC and BIC criteria, further affirming the enhanced model fit when incorporating environmental factors.

Additionally, the hypothesis that the shared frailty α_c in equation (6) is negligible is assessed through a LR test for the restriction H_0: $\theta = 0$, where θ is the variance of the probability distribution of α_c. The results reported in the diagnostic section of

Tables A.12 through A.18 indicate that the hypothesis is not rejected. Thus, the latent country variables do not induce domestic correlation in the failure risk for both energy and non-energy firms.

Our research highlights the distinct failure risk profiles between energy and non-energy firms, shedding light on the complexities involved in evaluating and predicting corporate failure risks accurately. These findings underscore the importance of considering various factors and employing appropriate models to assess failure risks in different sectors.

In summary, the analysis of the Cox proportional hazard models reveals nuanced insights into the failure risk of U.S. energy firms compared to their non-energy counterparts. When examining the models separately for energy and non-energy firms (Models III and IV), distinct patterns emerge. Consistent with the logit regression results, specific variables affect failure risk differently across the two types of firms.

Energy firms show a positive association between long-term debt and the risk of failure, underscoring their higher leverage and associated financial instability. This finding aligns with the capital-intensive nature of the energy sector, which often requires significant debt financing for exploration and infrastructure. The increased sensitivity to financial distress due to high leverage indicates that energy firms face greater risks related to their capital structure compared to non-energy firms.

The risk of failure for both energy and non-energy firms is significantly influenced by firm-specific indicators and the ESG combined score. However, there are notable differences in the magnitude and direction of these sensitivities between the two types of firms.

Based on the results, U.S. energy firms do not exhibit a uniformly higher or lower failure risk compared to non-energy firms. Instead, the failure risk for energy firms is influenced by specific factors. Energy firms face distinct challenges related to capital structure and input costs, making their failure risk more context-dependent compared to non-energy firms. They are more prone to failure due to financial leverage and volatility in input prices, but less affected by the size-related risks compared to non-energy firms.

1.5.2 Failure and insolvency risk

This subsection illustrates the enhanced insights provided by survival analysis in comparison to a conventional OLS regression using the z-score proxy. The z-score serves as the dependent variable in this analysis, while the independent variables encompass accounting metrics, macroeconomic factors, market structure variables, and environmental considerations. Tables A.19-A.21 display the estimation results derived from three distinct models: Model A for pooled U.S. firms, Model B specifically for U.S. energy firms, and Model C for U.S. non-energy firms. The interpretation of coefficient signs in this analysis diverges from the conventions observed in logit and survival analyses. In this context, a positive coefficient signifies that an increase in the predictor variable is associated with a higher z-score, suggesting a favourable impact on financial stability or reduced risk of failure. Conversely, a negative coefficient indicates that as the predictor variable increases, the z-score declines, implying a negative impact on financial stability and an increased risk of failure. These distinctions underscore the unique contributions of survival analysis to understanding the dynamics of financial health and corporate failure.

[Table A.19-A.21 around here]

In examining the z-score values in Table A.19, the analysis reveals a significant negative coefficient for the energy dummy variable (-77.7240, $p = 0.0007$). This finding indicates that, on average, energy firms have lower z-scores compared to their non-energy counterparts, suggesting that they are perceived as having a higher risk of financial failure. This result stands in contrast to the earlier findings from the survival analysis.

The lower z-scores for energy firms imply that despite their substantial size and potentially significant assets, these firms are more susceptible to financial distress. This heightened risk could be attributed to sector-specific factors such as high capital intensity, volatile input costs (like those for uranium), and regulatory uncertainties. Energy firms, especially those in the nuclear sector, face substantial challenges in passing on increased operational costs to consumers due to regulated pricing structures and long-term supply contracts. Additionally, the capital-intensive nature of the energy sector means that energy firms often operate with higher leverage, which can exacerbate their vulnerability to economic downturns and market fluctuations.

This discrepancy between the logit regression results and the z-score analysis highlights the importance of using multiple metrics to assess failure risk. While the logit regression may capture broader financial and market conditions, the z-score provides a more direct measure of a firm's financial stability by incorporating a range of income statement variables and macroeconomic factors. Thus, the lower z-scores for energy firms underscore the need to consider industry-specific characteristics and financial structures when evaluating corporate failure risk. It also suggests that energy firms' financial health might be more precarious than previously indicated, necessitating a closer examination of their capital structure, operational efficiency, and exposure to input cost volatility.

In the estimation results for Model A (Table A.19), Model B (Table A.20) and Model C (Table A.21), the coefficient for firm size (assets) is positive and highly significant

($p < 0.0000$), impacting both energy and non-energy firms. This suggests that larger firms tend to exhibit higher z-scores, which implies a lower risk of financial failure. This finding supports the view that larger firms are generally more financially stable. The increased z-score for larger firms may be attributed to several factors, including greater resource availability, enhanced capacity for diversification, and improved access to financing. Larger firms often benefit from economies of scale, which can lead to more robust financial health and a greater ability to absorb economic shocks. Additionally, the extensive asset base of larger firms can provide a buffer against financial distress, contributing to their overall stability and lower perceived failure risk. This result aligns with the established notion that firm size is positively correlated with financial stability, highlighting the protective benefits of scale and diversification in mitigating failure risk.

Additionally, the negative coefficient associated to the variable equity in Model A and Model C, respectively, is marginally significant, implying that higher equity levels slightly increase the risk of corporate failure. This is not consistent with the general expectation that stronger equity positions enhance financial stability, supporting the results from the logit regression analysis.

Similarly, the negative and statistically significant coefficient for stock prices observed in Models A and C indicates that higher stock prices are associated with an increased risk of corporate failure. This counter-intuitive result may reflect deteriorating investor confidence and negative market perceptions, where rising stock prices might signal overvaluation or market instability, potentially leading to increased financial vulnerability.

Furthermore, a consistent positive relationship between the Return on Assets (ROA) indicator and an increase in the z-score is evident across all models (Models A to C). This parallel trend aligns with findings from the survival analysis, reinforcing the role of ROA as a reliable predictor of the financial health of both energy and non-energy firms. Higher ROA values signify efficient asset utilization, indicating that firms are generating more income from their assets. This not only strengthens their overall financial position but also enhances their z-scores, affirming the consistent predictive power of ROA in assessing firm stability.

In Model C, the observed linkage between a higher level of equity over assets ratio and increased financial wealth for U.S. non-energy firms resonates with the survival analysis results. This finding implies that non-energy firms with greater equity levels are more adept at accumulating financial resources, thereby bolstering their financial health. The alignment between estimation results and survival analysis underscores the robustness and reliability of factors influencing failure risk, portraying a coherent narrative across different analytical approaches.

Moreover, this consistent alignment provides valuable insights into the factors contributing to corporate failure risk within both energy and non-energy sectors. It suggests that considerations such as efficient asset utilization and capitalization levels play pivotal roles in determining financial stability, transcending the differences between the two sectors.

Additionally, diverging from the insights gleaned from both logit and survival analysis, the coefficients associated with capital expenditure and long-term debt demonstrate a lack of predictive power concerning corporate failure across Model A to C.

Another notable departure from the logit and survival analysis arises from the insignificance of macroeconomic variables across all models, challenging the initial expectations. The lack of significance in these variables suggests that their impact on the z-score, and consequently on financial stability, is not as pronounced as implied by the logit survival analysis. This incongruity prompts a reevaluation of the role played by macroeconomic factors in determining the financial health of firms.

Similar to the previous results, the analysis reveals that GDP growth is associated with a decreased risk of corporate failure, particularly for energy firms (Model B), which is consistent with the findings from our logit and survival analyses. This suggests that periods of economic expansion benefit energy firms, potentially due to increased demand for energy and supportive macroeconomic conditions. However, the coefficient for GDP growth is negative and marginally significant in Model C, indicating that higher GDP growth is linked to slightly lower z-scores for non-energy firms. This finding contradicts the overall trends observed in the logit and survival analyses, where GDP growth was generally linked to decreased failure risk.

The more pronounced impact of GDP growth on non-energy firms compared to energy firms can be attributed to the differing sensitivities of these sectors to economic fluctuations. Non-energy firms, often operating in more cyclical industries, may be more directly affected by macroeconomic conditions such as GDP growth. In contrast, energy firms, particularly those in the nuclear sector, may benefit from more stable revenue streams due to long-term contracts or regulated pricing structures, providing a buffer against economic downturns. As a result, non-energy firms experience more acute financial stress during periods of economic expansion, leading to a more pronounced effect on their z-scores and overall risk of corporate failure.

The observed contradictions between the z-score analysis and the logit and survival analysis prompt a closer examination of the assumptions underpinning the z-score as a proxy for failure risk in both energy and non-energy firms. One compelling explanation for these discrepancies is the inherent assumption that the z-score holds equal validity across diverse industry landscapes. This assumption may not fully account for the unique operational intricacies and risk profiles present in energy firms compared to their non-energy counterparts.

Energy firms often contend with distinctive challenges, such as commodity price volatility, regulatory uncertainties, and geopolitical influences, which may not be adequately captured by a metric designed with conventional business models in mind. Consequently, the applicability of the z-score as a universal indicator of failure risk may be compromised when confronted with the specialized dynamics of the energy sector. The complex interplay of environmental factors, market uncertainties, and industry-specific risks may render the z-score less effective in accurately gauging the true risk of failure for energy firms.

Alternatively, the discrepancy may arise from the differing nature of risk considered by Ordinary Least Squares (OLS) models for the z-score and the survival models. OLS models primarily focus on insolvency risk, reflecting the ability of a firm to meet its short-term obligations. In contrast, survival models directly account for the occurrence of firm failures over a specified period. This distinction is crucial, as the z-score, while informative about insolvency risk, may not fully encapsulate the multifaceted dynamics leading to actual corporate failures.

Survival analysis, by design, factors in the time-to-failure dimension, considering not just the probability of insolvency but the temporal aspect of when failures occur. This temporal dimension adds granularity to the assessment of failure risk, capturing the evolving nature of risks over time.

Moreover, in contrast to the results from the logit and survival analyses, the coefficient for the ESG score is consistently negative across Models A to C, indicating a deterioration in financial health as the ESG score increases. Specifically, this suggests that higher ESG scores are associated with lower z-scores, which reflects a greater risk of corporate failure. The statistical significance of this coefficient highlights a potential paradox where firms with higher ESG scores may experience increased financial vulnerability. This finding emphasizes the necessity of incorporating ESG indicators into corporate failure analysis, as it underscores the complex relationship between ESG performance and financial stability. It suggests that while ESG considerations are critical for assessing a firm's sustainability and ethical practices, they may also have nuanced implications for financial health that warrant further investigation.

Additionally, the positive yet statistically insignificant coefficient for CO2 emissions suggests that CO2 does not exhibit predictive power in forecasting corporate failure in Models A and C. This finding contrasts with results from the logit and survival analyses, where increased CO_2 emissions were more strongly associated with failure risk. Interestingly, the results here hint at a potential inverse relationship, where firms with higher CO_2 emissions might exhibit greater financial resilience, as indicated by their higher z-scores. This counter-intuitive outcome could imply that firms with significant emissions often operate in energy-intensive, revenue-generating industries, which may afford them the financial stability to weather economic challenges. These findings challenge conventional assumptions and suggest that CO_2 emissions may serve as an indirect proxy for a firm's operational scale or profitability, rather than being a direct environmental or risk factor.

These findings underscore a critical limitation in relying on conventional proxies, originally crafted for traditional business models, when assessing failure risk, especially in the context of energy firms and the inclusion of environmental indicators. The novel evidence presented in this subsection reveals a nuanced reality where the insolvency risk measured by the z-score may not precisely align with the actual risk of failure, particularly within the distinctive operational landscape of energy firms.

The disparities observed in the relationship between the z-score and failure risk for energy and non-energy firms highlight the inadequacy of one-size-fits-all approaches in the realm of financial health evaluation. The unique characteristics of energy firms, coupled with the growing significance of environmental considerations, necessitate a reevaluation of established risk assessment metrics.

These results emphasize the need for a more nuanced and context-specific approach in evaluating the financial health of both energy and non-energy firms. A tailored assessment framework that considers industry-specific nuances, environmental factors, and the intricacies of the business model is imperative for a comprehensive understanding of failure risk. As we navigate the evolving landscape of corporate finance, these insights underscore the importance of adapting financial evaluation methodologies to the diverse and dynamic realities of contemporary business environments.

1.5.3 Network Analysis

In this sub-section, we explore the integration of our logit regression analysis, incorporating all the indicator variables, with network analysis to enhance our understanding of the data. A network, or graph, consists of nodes connected by edges. In an unweighted graph, the adjacency matrix is an $n \times n$ matrix where each entry (i, j) is either 1 or 0, indicating whether nodes i and j are connected. In a weighted graph, this entry reflects the strength of the connection between nodes (see Appendix A.1 for further details on the network analysis).

To integrate network analysis with our logistic regression model - which includes firm-specific, macroeconomic, energy market structure, and environmental variables - we first construct a network representation based on the correlation matrix of the numerical variables. This matrix is transformed into an adjacency matrix using a threshold of 0.5 to define the presence of edges. We then convert the adjacency matrix into a graph using the *igraph* package in *Rstudio*. In this network, nodes represent variables and edges signify the relationships between them.

Next, we compute the Fiedler value, which is the second smallest eigenvalue of the Laplacian matrix of the graph. This value measures the overall connectivity and robustness of the network. To obtain the Fiedler value, we first calculate the Laplacian matrix from the graph and then extract its eigenvalues. The Fiedler value provides insights into the network's resilience and the importance of individual nodes in maintaining overall connectivity.

Finally, to analyse the temporal dynamics of corporate failure, we aggregate the predicted probabilities of failure from our logistic regression model by fiscal year. This aggregation allows us to assess annual trends in the likelihood of corporate failure for both energy and non-energy firms, offering valuable insights into how failure probabilities evolve over time.

[Table A.22-A.23 around here]

Table A.22 presents the average predicted probability of corporate failure for energy firms from 2010 to 2022. The data reveals a significant decline in the average predicted probability of failure, decreasing from 40.1% in 2010 to 0.40% in 2022. This downward trend indicates a marked improvement in the financial stability of energy firms over the observed period. The steady annual decrease, particularly notable between 2018 and 2020, suggests potential positive shifts within the energy sector, such as improved economic conditions, enhanced financial management, or effective policy interventions that have benefitted these firms.

Similarly, Table A.23 displays the average predicted probability of failure for non-energy firms during the same period. The average probability of failure decreased from 46.4% in 2010 to 0.36% in 2022, reflecting a significant reduction in risk. This trend mirrors the improvements observed in energy firms, indicating that non-energy firms have also enhanced their financial stability over the past decade. The most substantial reduction in failure probability occurred between 2018 and 2020, which may be attributed to various factors, including better financial practices, favourable economic conditions, or positive industry dynamics.

Additionally, the Fiedler value for the network constructed from the correlation matrix of numerical variables in both energy and non-energy firms is approximately 2. The Fiedler value, which represents the second smallest eigenvalue of the Laplacian matrix, gauges the overall connectedness of the network. A Fiedler value of 2 suggests a moderate level of connectivity among the variables, indicating that while there is a reasonable degree of interconnectedness, there is potential for further strengthening the network's structure.

Comparing the two sectors, both exhibit a clear decline in failure probability over time; however, energy firms show a more pronounced and consistent reduction. Specifically, the failure probability for energy firms dropped from 40.1% in 2010 to 0.40% in 2022, while for non-energy firms, it declined from 46.4% to 0.36% over the same period. Interestingly, although energy firms demonstrate a steeper overall decline, non-energy firms appear to have achieved slightly greater stability by 2022. The sharp decrease in failure probability for both sectors in the last three years highlights significant improvements in their financial health. Despite these trends, non-energy firms consistently exhibit a higher probability of failure compared to their energy counterparts. This disparity may stem from sector-specific challenges faced by non-energy firms, such as greater exposure to market competition and less insulation from macroeconomic fluctuations, as opposed to the energy sector, which may benefit from more uniform economic improvements and structural advantages. This distinction highlights the importance of developing tailored risk management strategies that address the unique vulnerabilities and operational dynamics of each sector.

Overall, this analysis highlights that while both sectors have experienced enhanced stability, energy firms have demonstrated more significant progress. The combination of decreasing failure probabilities and a moderate Fiedler value indicates improving financial performance and resilience among both energy and non-energy firms, with a network structure showing moderate interconnectedness.

1.6 Conclusion

Over the past three decades, U.S. energy firms have faced numerous influences on their corporate performance, driven by shifts in the energy industry, fluctuations in commodity prices, changes in regulatory frameworks, and growing environmental concerns. These factors have significantly impacted the risk of corporate failure for energy companies, leading to a heightened interest in understanding the determinants of failure risk.

In this research, we conduct a comprehensive analysis to explore the failure risk profiles of U.S. energy and highly dependent energy firms in comparison to U.S. non-energy firms. Our objective is to illuminate the complexities involved in accurately evaluating and predicting corporate failure risks. By using a variety of firm-level, macroeconomic, market structure, and environmental indicators, we reveal essential insights into the distinct nature of failure risks between these two types of firms. In doing so, we challenge the orthodoxy of conventional models and embrace the dynamism inherent in assessing corporate failure risk.

This paper contributes to the growing empirical literature on corporate failure prediction. We employ a logit and survival analysis offering several advantages over conventional approaches such as z-score measures, MDA techniques, and distance to default (Pappas et al. (2017)). Survival models overcome the limitations of relying on z-scores when predicting corporate failure. Moreover, survival analysis is based on models where the time-to-failure is the stochastic variable of interest, effectively treating failure risk as a time-varying latent variable. Consequently, this approach does not impose specific distributional assumptions on the estimates, enhancing the robustness of our findings.

Our empirical investigation yields several key findings that advance our understanding of failure risk for U.S. firms. Firstly, we provide both unconditional and conditional measures of failure risk, differentiating between energy and non-energy sectors. Secondly, our analysis highlights significant contrasts in how these firm types respond to accounting variables, macroeconomic indicators, market structure, and environmental factors. Thirdly, we evaluate the predictive power of various models by comparing logit and survival regressions with z-score measures derived from both pooled data and sector-specific information. Lastly, we demonstrate that logit and survival models offer distinct and nuanced insights compared to z-score OLS regressions, which are commonly used in existing literature. This underscores the necessity of employing diverse analytical approaches to accurately assess firm stability and failure risk.

Our research provides a comprehensive assessment of failure risk profiles for U.S.

energy and non-energy firms using logit, survival, and network analyses. The logit and survival analyses reveal that U.S. energy firms, despite their substantial size and stable revenue streams, exhibit distinct failure risk profiles compared to non-energy firms. Energy firms are more sensitive to financial leverage and input cost volatility, while factors such as GDP growth and ESG scores impact failure risk differently across these sectors. Specifically, the logit regression results indicate that energy firms generally have a lower risk of failure compared to their non-energy counterparts, even when accounting for firm-specific characteristics, macroeconomic indicators, market structure, and environmental factors. This result emphasizes the importance of incorporating sector-specific nuances into risk assessment models. In survival analysis, the Cox proportional hazard models further confirm these sector-specific differences. While larger firms across both sectors generally face higher failure risks, a reflection of the "too-big-to-fail" concept, energy firms are less sensitive to size-related risks compared to non-energy firms. Energy firms are more exposed to risks associated with high financial leverage and volatile input prices, such as uranium, but show less pronounced sensitivity to firm size. In contrast, revenue growth impacts non-energy firms' failure risk more significantly, suggesting differences in financial practices and revenue structures between the sectors.

The network analysis offers valuable insights into the evolution of failure probabilities over time. Between 2010 and 2022, both energy and non-energy firms experienced a significant decline in their average predicted probabilities of failure. For energy firms, the probability decreased sharply from 40.1% to 0.40%, while for non-energy firms, it fell from 46.4% to 0.36%. This overall reduction highlights notable improvements in financial stability across both sectors, with non-energy firms demonstrating a particularly pronounced decline in failure risk, especially between 2021 and 2022. These findings point to sector-specific advancements or enhanced financial management practices. However, in 2022, energy firms exhibited a slightly higher probability of failure compared to their non-energy counterparts, indicating persistent vulnerabilities unique to the energy sector.

Moreover, we document important differences in the sensitivity of failure risk between the two firm types. Specifically, the volatility in oil and gas prices significantly impacts energy firms' revenues; sharp declines in these prices can reduce profitability and strain cash flows, increasing default risk. Persistent price volatility introduces uncertainty, complicating financial planning and investment strategies.

Leverage becomes a double-edged sword for energy companies. Higher leverage exacerbates the failure risk for energy firms. Interestingly, the fluctuations in the global spot price of uranium are significantly associated with an increased risk of corporate failure for energy firms. In contrast, both energy and non-energy firms experience increased failure risk with rising uranium prices. For energy firms, particularly those in the nuclear sector, high uranium costs impact profitability and operational stability, highlighting the significant role of volatile input prices in their financial health. The study underscores that for nuclear energy firms in the U.S., increasing uranium costs may undermine economic viability and raise concerns about the sustainability of nuclear energy investments in the face of volatile input prices.

While the ESG combined score emerges as a shield against failure for both, underscoring the significance of incorporating environmental indicators in the analysis. This is in line with some studies that concluded that by including environmental efficiency improves corporate performance (Pätäri et al. (2014), Arslan-Ayaydin and Thewissen (2016), Doumpos et al. (2017), Arslan-Ayaydin and Thewissen (2016), Cantore, Calı, and Velde (2016)).

Significantly, the CO_2 emissions indicator demonstrates a substantial impact on both energy and non-energy firms across all the models. The inclusion of environmental indicators in survival analysis offers crucial insights into the resilience and sustainability of firms across industries. By considering factors such as U.S. total CO_2 emissions, firms can better understand and anticipate the implications of environmental regulations, shifting consumer preferences, and broader sustainability trends on their long-term viability. Incorporating environmental indicators into survival analysis enables a more comprehensive assessment of the multifaceted risks and opportunities facing modern businesses, fostering proactive strategies for adaptation and resilience in an increasingly environmentally-conscious global economy. Furthermore, as environmental considerations become integral to stakeholder expectations and regulatory frameworks, analysing the impact of environmental indicators on corporate survival provides valuable guidance for strategic decision-making and risk management in the corporate finance world.

Additionally, stricter environmental regulations can escalate operational costs and require substantial capital investments to ensure compliance. Policy shifts, such as increased incentives for renewable energy or higher carbon taxes, further exacerbate the financial challenges faced by traditional energy firms. Moreover, both physical climate risks and transition risks can damage infrastructure and disrupt operations, adding another layer of vulnerability. These findings underscore the urgent need for a comprehensive reevaluation of regulations and policies affecting the energy sector. Policymakers must acknowledge the potential broader economic repercussions of energy sector failures and consider implementing proactive measures to mitigate these risks, thereby enhancing financial stability and safeguarding the economy against sector-specific shocks.

Therefore, the differential impact of environmental indicators highlights the necessity for tailored environmental policies that consider sector-specific nuances. A one-size-fits-all approach to environmental regulations may not be effective, and policies should be finely tuned to the distinct characteristics of the U.S. energy sector. This aspect emphasises the role of policymakers in fostering sustainability practices within the industry and ensuring that environmental regulations are aligned with the unique challenges faced by energy firms.

Furthermore, our analysis reveals that increased market concentration within the energy sector heightens the likelihood of failure for both energy and non-energy firms. Additionally, the risk of failure for energy firms is affected by inflation, highlighting the complex interaction between economic conditions and corporate vulnerability. Interestingly, traditional financial ratios appear to have a limited impact on the risk profile of energy firms, as evidenced by both logit and survival analyses. This suggests that other factors, potentially including market dynamics and economic variables, play a more substantial role in shaping the failure risk for firms in this sector.

In summary, our research provides valuable insights into the failure risk profiles of energy, highly dependent energy, and non-energy firms in the U.S., highlighting the importance of considering various factors and employing appropriate models in predicting corporate failure risks accurately. These findings contribute to a deeper understanding of the complexities involved in risk assessment and management across different sectors. Thus, the heightened vulnerability of energy firms raises alarms, demanding a revaluation of policies and regulations that govern the energy sector in the U.S.

Despite increasing attention to climate issues, many U.S. states remain hesitant to adopt comprehensive climate policies (Bromley-Trujillo et al., 2016; Egan and Mullin, 2017; Benegal and Scruggs, 2018), largely due to partisan divides and the considerable lobbying influence of fossil fuel and utility interests. These findings point to the urgent need for a collaborative effort between regulatory bodies and industry stakeholders to develop adaptive risk management strategies that can evolve with the changing dynamics of the energy sector across the U.S. Such strategies should focus on mitigating systemic risks and ensuring resilience in an increasingly interconnected corporate landscape.

Our findings reveal that U.S. energy firms do not exhibit a uniformly higher or lower risk of failure compared to non-energy firms. Instead, their failure risk is context-specific, driven by factors such as capital structure and input cost volatility. While energy firms are more exposed to financial leverage and commodity price fluctuations, they are relatively less sensitive to size-related risks. In contrast, non-energy firms are more vulnerable to revenue shocks and macroeconomic pressures. These asymmetries highlight the importance of accounting for sector-specific risk sensitivities when modelling financial distress and reinforce the need to treat firm heterogeneity explicitly in corporate failure prediction.

The distinct failure dynamics between energy and non-energy firms underscore the broader policy implications of energy sector instability. Policymakers and industry leaders must adopt more targeted risk management frameworks that reflect the sector's structural characteristics, especially as energy markets evolve amid the low-carbon transition. By refining how we assess and manage failure risk, this research contributes to building a more resilient and sustainable energy sector, critical to the stability of the broader economy.

Looking ahead, future research should investigate potential spillover effects between the energy sector and other industries. In particular, examining whether distress in the energy sector can serve as an early warning signal for failures elsewhere would enhance our understanding of systemic risk and sectoral interdependencies. Insights from such analysis could inform the development of integrated early warning systems and support more effective macro-prudential policy design.

Appendix A

Chapter 1

A.1 Network Centrality Analysis of Corporate Failure Risk

In this subsection, we aimed to assess the potential risk of corporate failure among firms in our dataset by employing the previous logistic regression model and visualizing inter-firm relationships using network analysis[1]. In the context of corporate failure, centrality metrics help determine which firms are the most connected, most influential, and how failure could propagate through the network. By analysing the centrality of firms, particularly distinguishing between energy and non-energy firms, we can better understand the systemic risk within the network and identify the key influencers of corporate failure. One particularly insightful centrality measure used in this analysis is

[1]The logistic regression model used to estimate the probability of failure $p_i(t)$ for firm i at time t is given by:

$$p_i(t) = \frac{1}{1 + \exp\left(-\left(\beta_0 + \beta_1 X_{1i}(t) + \beta_2 X_{2i}(t) + \cdots + \beta_k X_{ki}(t)\right)\right)}$$

where $X_{1i}(t), X_{2i}(t), \ldots, X_{ki}(t)$ represent the firm-specific, macroeconomic, and market variables at time t.

To construct the network, we calculate the distance between the probabilities of failure for firms i and j at time t:

$$d_{ij}(t) = |p_i(t) - p_j(t)|$$

Using a threshold ϵ, the elements of the adjacency matrix $A_{ij}(t)$ are defined as:

$$A_{ij}(t) = \begin{cases} 1 & \text{if } d_{ij}(t) \leq \epsilon \\ 0 & \text{otherwise} \end{cases}$$

eigenvector centrality (Barigozzi, Hallin, et al. (2021)). Eigenvector centrality[2] not only considers the number of connections a node has but also factors in the importance of the nodes it is connected to. This is key for understanding systemic risk in our analysis.

To implement the concept of centrality in our analysis using *Rstudio*, we combined survival analysis, specifically through a logistic model, with network analysis techniques. The primary goal was to assign weights to firms based on their centrality within the network, with a particular focus on the top 100 firms, comprising 50 energy firms and 50 non-energy firms, ranked according to their predicted probability of failure.

The logistic regression model used to predict the likelihood of corporate failure was built on pooled data of energy and non-energy firms. It incorporated several key financial metrics, including total assets, equity, liabilities, revenue, and performance ratios such as Return on Assets (ROA) and Return on Equity (ROE). In addition to firm-level data, external macroeconomic indicators, such as GDP growth and inflation rates, were included, along with environmental indicators like the ESG combined score and CO2 emissions. The model generated predicted probabilities of failure for each firm, which served as the basis for subsequent network analysis.

Following the prediction of failure probabilities, we identified the top 100 firms with the highest likelihood of failure. To ensure a balanced representation, we divided the firms equally into two categories: the top 50 energy firms and the top 50 non-energy firms based on their failure probabilities. This split allowed us to examine potential systemic risks within both the energy and non-energy sectors. This approach ensures that the analysis captures the most vulnerable firms across sectors, providing a clearer picture of how risk is distributed between energy and non-energy firms. Understanding these high-risk firms' positions within the corporate landscape is crucial for identifying potential vulnerabilities and assessing their contribution to systemic risk, particularly in industries that may disproportionately influence broader economic stability.

To explore the relationships among these firms, we used the *igraph* package in *Rstudio* to create a directed network graph. The network was constructed by first generating a

[2] Eigenvector centrality accounts for the influence of a firms connections. Eigenvector centrality assigns higher scores to firms that are connected to other influential firms. The eigenvector centrality $C_i(t)$ of firm i at time t is given by:

$$C_i(t) = \frac{1}{\lambda} \sum_{j=1}^{n} A_{ij}(t) C_j(t)$$

For each firm, the time-varying eigenvector centrality is represented as:

$$C_i(t) = \frac{1}{\lambda(t)} \sum_{j=1}^{n} A_{ij}(t) C_j(t), \quad t = 2010, 2011, \ldots, 2020$$

correlation matrix for the numerical variables in the dataset, which was then transformed into an adjacency matrix. The adjacency matrix represented the connections between firms based on shared financial metrics, indicating how one firm's failure might influence others.

[Table A.24 and Figure A.9 around here]

Table A.24 and Figure A.9 present the average eigenvector centrality of the top 50 energy and top 50 non-energy firms from 2010 to 2022, where eigenvector centrality serves as a proxy for systemic risk within the corporate failure network. Higher eigenvector centrality values suggest that a firm is more central and influential within the network, with greater interconnectedness and potential to affect other firms. Thus, a higher eigenvector centrality score indicates a greater systemic risk.

Throughout most of the analysed period, non-energy firms consistently exhibit higher average eigenvector centrality than energy firms, implying that non-energy firms are more central in the corporate failure network. This heightened centrality suggests that the failure of non-energy firms could propagate more extensively, presenting a higher systemic impact compared to the energy sector. During the early years (2010–2016), non-energy firms maintained noticeably higher centrality scores, suggesting that their systemic risk was relatively elevated at the onset (Table A.24). The eigenvector centrality of non-energy firms shows a steady upward trend, starting at 0.601 in 2010, increasing from 0.818 in 2016 to 1.000 by 2021-2022. This trend likely reflects a growing interdependence among non-energy firms over time, positioning them as progressively more influential within the failure network.

In contrast, energy firms exhibit more variability and a less consistent rise in centrality, starting at a lower 0.517 in 2010 and gradually increasing to 0.972 by 2019, reaching the highest value in 2021 (1.000). This pattern suggests that, while energy firms were initially less interconnected, they have become increasingly integrated into the network, potentially due to shifts in market dynamics or stronger dependencies with non-energy sectors.

In the latter part of the period, particularly from 2017 to 2022, the centrality scores for both energy and non-energy firms converge, reaching values around or above 0.9. This convergence implies that by 2017, both sectors had become similarly central within the failure network, suggesting that failures in either sector could now have comparable systemic impacts. This shift could result from strengthened cross-sector linkages or heightened interdependencies that emerged over the years.

The analysis of eigenvector centrality provides valuable insights into the evolving systemic risk of corporate failures across sectors. While energy firms initially held lower centrality scores, their increasing importance in the network over time, as indicated by scores approaching parity with non-energy firms, suggests a heightened risk of cascading failures from the energy sector. The convergence of eigenvector centrality values by 2017–2022 points to a more interconnected corporate environment where cross-sector dependencies are substantial, making both sectors critical to understanding and managing systemic risk.

[**Figure A.10 around here**]

Figure A.10 illustrates the network based on eigenvector centrality as a measure of interconnectedness among the top 50 energy and 50 non-energy firms in 2022. This visualization reinforces the quantitative findings from 2022, where both energy and non-energy firms exhibit high centrality scores. The close positioning of firms from both sectors within the network supports the interpretation that systemic risk is now comparable across these sectors. The convergence in centrality values, as observed in previous tables and graphs, is visually confirmed by the interwoven connections between energy and non-energy firms.

In terms of density and clustering, non-energy firms (depicted as blue nodes) are densely clustered and display high interconnectivity, indicating a higher likelihood of failure propagation within this sector. Conversely, energy firms (shown as red nodes), while also interconnected, exhibit somewhat less clustering than non-energy firms. This relatively lower density suggests that failures within the energy sector may be less likely to propagate widely, or that energy firms are not as embedded within the overall network structure as non-energy firms.

Non-energy firms occupy more central positions in the network, consistent with their higher average eigenvector centrality values for 2020 (as presented in Table A.24). Central nodes signify firms that are more influential in the propagation of failure across the network, affirming that non-energy firms carry a greater systemic risk in terms of interconnectedness. Although energy firms are generally less central, many still demonstrate significant connectivity. Several energy firms are located near the network's core, suggesting that their failures could have substantial effects on nearby non-energy firms, underscoring their systemic influence.

The larger node sizes, representing higher predicted probabilities of failure, emphasize the prominence of certain non-energy firms. This implies that individual non-energy firms hold a considerable systemic risk. The diminishing visual separation between energy and non-energy firms indicates that failures within one sector could now more easily affect the other. This convergence of interdependence supports the trend of increasing cross-sectoral linkages, as evidenced by the similar eigenvector centrality values observed for both groups in 2022.

In summary, by 2022, the network reveals minimal distinction between energy and non-energy firms concerning systemic risk. Failures within either sector have the potential to create cascading effects across the network, impacting firms across both sectors due to their high degree of interconnectedness. This convergence in centrality scores highlights an increasingly interdependent corporate environment, where cross-sector vulnerabilities make both energy and non-energy firms equally critical to understanding and managing systemic risk.

A.2 Tables and Figures

	Total Number of firms	Number of distress cases (m_D)	Total number of observations (m)	Distress rate (%)	% Of the total sample
Energy Firms					
US	1,672	635	12,960	0.0490	0.0066
Non-Energy Firms					
US	9,130	3,618	82,783	0.0437	0.0378
Total	10,802	4,253	95,743		

Table A.1: **Sample decomposition by country, according to their SIC codes.** Note: m_D represents the number of distress cases, m represents the total number of observations, considering both energy and non-energy firms. DR represents the distress rate (m_D/m).

Table A.2: **Dependent and explanatory variables used in the analysis.** The table shows the variables considered in the analysis and their definitions.

Name	**Type**	**Definition**
Failure	Qualitative (dummy variable)	Binary indicator equal to 1 for failed firms in the year immediately prior to the failure event 0 in all other years.
Energy firms	Qualitative (dummy variable)	Binary variable equal to 1 if the firm is an energy firm, 0 otherwise.
Assets	Balance Sheet	Logarithm of total earning assets represents the size of the firm. This item represents current assets plus net property, plant, and equipment plus other non-current assets, including intangible assets, deferred items and investments and advances.

Continued on next page

Table A.2 – continued from previous page

Name	Type	Definition
Common Equity – Total	Balance Sheet	Common equity. This item represents the common shareholders' interest in the company. This item is a component of Shareholders' Equity - Total (SEQ).
Net Income	Income statement	Net Income represents the firm net income used in the comprehensive income calculation, excluding net income that does not match the reported beginning net income number in the comprehensive income calculations.
Total Liabilities	Balance Sheet	Total Liabilities represents current liabilities plus long-term debt plus other non-current liabilities, including deferred taxes and investment tax credit.
Total Revenue	Balance Sheet	Total amount of money earned by a company from its primary business operations, it provides an essential measure of a company's ability to generate income from its core business activities.
Price Close – Annual – Fiscal	Balance Sheet	Close price refers to the closing price of a financial asset (such as a stock or commodity) at the end of the fiscal year. In this research we report the logarithm of close price.
Capital Expenditure	Balance Sheet	Refers to the funds a firm invests in upgrading, acquiring, or maintaining physical assets such as buildings, property, equipment, or technology that will be used for long-term business operations. These expenditures are essential for energy firms to sustain and grow their operations.
Long Term Debt	Balance Sheet	Represents financial obligations that a firm is obligated to repay over a period exceeding one year.

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Table A.2 – continued from previous page

Name	Type	Definition
Equity/Assets	Financial Ratio	Measures the amount of protection the firm enjoys by its equity.
ROA	Financial Ratio	ROA measures how effectively a company is using its assets to generate profits. The ratio is calculated by dividing a company's net income by its total assets.
ROE	Financial Ratio	ROE measures how effectively a company is using its shareholder's equity to generate profits. The ratio is calculated by dividing a company's net income by its shareholder's equity.
Dividends per Share	Financial Ratio	This indicator measures the amount of dividends distributed by a company to its shareholders on a per-share basis. It represents the portion of a company's profits that is paid out to shareholders as cash dividends. It helps investors evaluate the cash flow potential of a company and compare dividend payouts across different companies and industries.
ESG Combined Score (Score 1-100)	Environmental Indicator	The ESG Combined Score is an overall company score based on the reported information in the environmental, social and governance pillars (ESG Score) with an ESG controversies overlay. It provides an overall assessment of a company's performance in these areas, indicating its commitment to sustainability, responsible business practices, and ethical conduct. The higher the score the better is the firm performance.

Continued on next page

Table A.2 – continued from previous page

Name	Type	Definition
Growth of Real GDP (annual %)	Macroeconomic	Growth rate of inflation corrected GDP. This indicator refers to the percentage increase in the inflation-adjusted value of a country's total output of goods and services over a specific period. Real GDP growth is used as a key indicator of economic growth and is often used to assess the overall health and performance of a country.
Inflation, GDP deflator (annual %)	Macroeconomic	Year-on-year logarithm change of the GDP deflator. Measures the average percentage change in the prices of goods and services consumed by households over a period of one year. Inflation is often considered a key macroeconomic indicator because it reflects the overall health of an economy and can impact the purchasing power of individuals and businesses.
Oil Prices	Macroeconomic	The logarithmic of the WTI crude oil prices provides a measure of the percentage change in the price of crude oil from one year to the next, considering the compounding effect of returns over time. This indicator variable is useful for analysing trends and patterns in crude oil prices, and can be used in a variety of applications, including forecasting, risk management, and investment analysis.
Uranium Prices	Macroeconomic	The logarithmic of the Uranium spot price in U.S. Dollars. The value represents the benchmark prices which are representative of the global market. They are determined by the largest exporter of a given commodity. Prices are period averages in nominal U.S. dollars.

Continued on next page

Table A.2 – continued from previous page

Name	**Type**	**Definition**
Investment Freedom Index (Score 1-100)	Macroeconomic	The Investment Freedom Index is a measure of a country's regulatory environment for foreign investment. Each country is given a score out of 100 based on its performance in these four areas, with higher scores indicating greater investment freedom. Overall, the Investment Freedom Index is a valuable tool for understanding the investment climate in different countries, and for making informed investment decisions.
Sector Concentration	Market Structure	Herfindahl index computed as the sum of squared market shares (asset wise) of firms in U.S. per year.
Energy Firm Share	Market Structure	Market share of energy firms per country per year.
CO2 Emissions (Kg per PPP $ of GDP)	Environmental Indicator	CO2 emissions (Kg per PPP $ of GDP) is a measure of the carbon intensity of a country's economy, which represents the amount of carbon dioxide emitted per unit of economic output. This indicator provides a measure of a country's environmental impact relative to its economic output.

Table A.3: **Descriptive statistics.** The table reports the descriptive statistics for the variables considered in our analysis. The observation period is 2010 to 2022. The $ denotes US dollars. The St. Dev is the standard deviation.

Name	**Units**	**Mean**	**St. Dev**	**Min**	**Max**	**Median**	**Obs.**
Panel A: Firm-specific indicators							
Energy Dummy	$m	0.1354	0.3421	0.0000	1.000	0.0000	95,743

Continued on next page

Table A.3 – continued from previous page

Name	Units	Mean	St. Dev	Min	Max	Median	Obs.
Log (Assets) - size	$m	6.081	3.230	-6.908	15.275	6.540	95,743
Equity	$m	2,444.55	11,206	-13,9965	28,4434	214.71	95,743
Net Income	$m	259.40	1,800	-23,528	99,803	0.0000	95,743
Liabilities	$m	12,083	116,971	0.00	4,245,011	365	95,743
Log (Close Price)	$m	3.964	3.457	-9.210	14.659	3.997	95,743
Capital Expenditure	$m	303.05	1619	-3,258	63,645	6.19	95,743
Long Term Debt	$m	5303	94,498	0.0000	4,211,684	63	95,743
Revenue	$m	4,017.7	17,494	-24,954.7	569,962.0	282.6	95,743
Equity/Assets	$m	-3.355	126.0	-15,566	14.500	0.358	95,743
ROA	$m	-2.513	133.6	-29,700.5	13,583	0.0000	95,743
ROE	$m	-0.45	115.6	-31,837	7,322.14	0.0400	95,743
Div/Shares	$m	1,175	59,110	-14.0	8,250,000	0.0000	95,743
ESG Combined Score	Score	23.51	22.99	0.0000	95.75	21.48	95,743
Panel B: Macroeconomic indicators							
Growth of Real GDP	%	2.139	1.839	-2.768	5.945	2.281	13
Inflation (log-difference of the GDP deflator)	%	0.5706	0.9715	-2.132	2.080	0.5945	13
Log (Oil Prices)	$m	4.218	0.3320	3.668	4.585	4.221	13
Log (Uranium Price)	$m	3.536	0.3116	2.956	4.105	3.560	13
Investment Freedom Index	Score	75.87	1.4806	72.10	78.00	76.00	13
Panel C: Market structure indicators							

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Table A.3 – continued from previous page

Name	Units	Mean	St. Dev	Min	Max	Median	Obs.
Sector Concentration (Herfindahl index)	%	0.00009	0.000008	0.00008	0.0001	0.00008	13
Energy Firm Market Share	%	0.1045	0.0074	0.0906	0.1134	0.1064	13
Panel D: Environmental indicators							
CO2 Emissions	Kg/$m	0.2744	0.0426	0.2051	0.3583	0.2635	13

Table A.4: **Accounting profile by firm category.** The table summarizes the accounting profiles according to firm type (energy vs. non-energy) and/or operating status (survive/fail) and reports the t-test on the mean differences. All amounts are in US$ millions except for financial ratios that are in percentage and the ESG combined score (0-100 score). *, **, *** denote significance of the t-statistic for the mean equality of each pair of columns from left to right at the 10%, 5%, and 1% levels, respectively.

	I	**II**	**III**	**IV**	**V**		**VI**		**IX**		**X**	
	Energy	**Non-energy**	**Survive**	**Fail**	**Energy**		**Non-Energy**		**Survive**		**Fail**	
					Survive	**Fail**	**Survive**	**Fail**	**Energy**	**Non-Energy**	**Energy**	**Non-Energy**
Number of Firms	12,960	82,783	71,190	24,554	9,840	3,120	61,350	21,433	9,840	61,350	3,120	21,433
Firm-Specific Indicators												
Assets	6.561	6.005***	6.316	5.397***	6.905	5.478***	6.316	5.398***	6.905	6.316	5.478***	5.398***
Equity	6005	2190***	3019	776.2***	5030	1028***	3019	776***	5030	3019	1028***	776***
Net Income	337.4	247.2***	333.4	44.82***	440.2	13.57***	333	44.82***	440.2	333	13.57***	44.82***
Liabilities	7037	12873***	15489	2207***	8731	1694***	15489	2207***	8731	15489	1694***	2207***
Price	1.311	4.380***	4.082	3.622***	1.386	1.074***	4.082	3.621***	1.386	4.082	1.074***	3.621***
Capital Expenditure	861.3	197.8***	371.4	102.6***	1035	311.3***	371.4	102.6***	1035	371.4	311.3***	102.6***
Long Term Debt	3051	5655***	6864	773.6***	3709	972.1***	773.6	6864***	3709	773.6	972.1***	6864***
Revenue	5812	3736***	4985	1212***	7264	1233***	4985	1212***	7264	4985	1233***	1212***
Equity/Assets	-6.616	-2.8***	-3.201	-3.799	-6.941	-5.591	-3.201	-3.799	-6.941	-3.201	-5.591	-3.799
ROA	-3.358	-2.381*	-2.418	-2.788	-2.268	-6.798	-2.418	-2.788	-2.268	-2.418	-6.798	-2.788
ROE	-0.0272	-0.5178	-0.511	-0.2782	-0.045	0.0291	-0.5111	-0.2782	-0.045	-0.5111	0.0291	-0.2782
Dividend/Shares	3154	865.1	1540	114.5***	4150	11.22***	1540	114.5***	4150	1540	11.22***	114.5***
ESG Combined Score	19.64	24.12***	25.52	17.68***	21.19	14.74***	25.52	17.67***	21.19	25.52	14.74***	17.67***

Table A.5: **Pooled Firms (Model I):** The logit regression model based on firm specific variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for pooled firms (Model I). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.3077	0.0221	-59.302	0.0000 ***
Log Assets	-0.01396	0.0130	-1.074	0.2830
Dummy Energy	-0.1074	0.0286	-3.755	0.0002 ***
Equity	-0.4725	0.0555	-8.509	0.0000 ***
Log Price	-0.0413	0.0119	-3.465	0.0005 ***
Net Income	-0.1085	0.0349	-3.112	0.0019 **
Liabilities	-0.2965	0.1664	-1.782	0.0747 *
Revenue	-0.3397	0.0496	-6.849	0.0000 ***
Equity/Assets	0.0062	0.0086	0.721	0.4706
ROA	0.0022	0.0076	0.291	0.7713
ROE	0.0049	0.0096	0.511	0.6094
Div/Share	-0.7750	0.2135	-3.629	0.0003 ***
ESG Combined Score	-0.2370	0.0107	-22.078	0.0000 ***
Capital Expenditure	0.1295	0.0381	3.397	0.0007 ***
Long Term Debt	-2.5535	0.5049	-5.057	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7482
Sensitivity	0.9998
Specificity	0.0000
Balanced Accuracy	0.4999

Diagnostics

McFadden's R^2	0.5791
AIC	71,635
Total Observations	65,411

Table A.6: **Pooled Firms (Model I):** The logit regression model based on firm specific variables and macroeconomic variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for pooled firms (Model I). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.4274	0.0217	-65.730	0.0000 ***
Log Assets	0.0218	0.0134	1.624	0.1043
Dummy Energy	-0.1215	0.0301	-4.040	0.0001 ***
Equity	-0.3807	0.0573	-6.647	0.0000 ***
Log Price	0.0395	0.0126	3.142	0.0017 **
Net Income	-0.2009	0.0381	-5.279	0.0000 ***
Liabilities	-0.3367	0.1752	-1.922	0.0546 .
Revenue	-0.4319	0.0520	-8.307	0.0000 ***
Equity/Assets	-0.0019	0.0085	-0.227	0.8201
ROA	0.0098	0.0097	1.012	0.3114
ROE	0.0037	0.0096	0.382	0.7021
Div/Share	-0.8188	0.2273	-3.602	0.0003 ***
ESG Combined Score	-0.3189	0.0112	-28.476	0.0000 ***
Capital Expenditure	0.0416	0.0401	1.038	0.2993
Long Term Debt	-1.1613	0.4770	-2.434	0.0149 *
GDP Growth (annual %)	0.0105	0.0130	0.806	0.4200
Log Inflation	-0.4286	0.0114	-37.474	0.0000 ***
Log oil prices	0.7473	0.0164	45.444	0.0000 ***
IFI	0.6603	0.0171	38.542	0.0000 ***
Log Uranium	-0.3118	0.0174	-17.950	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7583
Sensitivity	0.9686
Specificity	0.1326
Balanced Accuracy	0.5506

Diagnostics

Adjusted R^2 (McFadden R^2)	0.5503
AIC	65,436.0
Total Observations	95,743.0

Table A.7: **Pooled Firms (Model I):**The logit regression model based on firm specific variables, macroeconomic variables and energy market structure variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for pooled firms (Model I). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\lvert z\rvert)$
(Intercept)	-1.4927	0.0219	-68.052	0.0000 ***
Log Assets	0.0319	0.0135	2.359	0.0183 *
Dummy Energy	-0.1442	0.0304	-4.738	0.0000 ***
Equity	-0.3593	0.0582	-6.177	00.0000 ***
Log Prices	0.0504	0.0128	3.951	0.0000 ***
Net Income	-0.2335	0.0394	-5.931	0.0000 ***
Liabilities	-0.3792	0.1788	-2.121	0.0339 *
Revenue	-0.4469	0.0525	-8.517	0.0000 ***
Equity/Assets	-0.0047	0.0086	-0.543	0.5869
ROA	0.0098	0.0100	0.984	0.3249
ROE	0.0058	0.0120	0.486	0.6273
Div/Share	-0.8459	0.2352	-3.596	0.0003 ***
ESG Combined Score	-0.3410	0.0113	-30.115	0.0000 ***
Capital Expenditure	0.0209	0.0402	0.520	0.6029
Long Term Debt	-0.8591	0.4668	-1.840	0.0657 *
GDP Growth (annual %)	0.0746	0.0167	4.456	0.0000 ***
Log Inflation	0.3543	0.0229	15.478	0.0000 ***
Log oil prices	-0.7127	0.0406	-17.560	0.0000 ***
IFI	0.3411	0.0212	16.060	0.0000 ***
Log Uranium	0.5226	0.0375	13.946	0.0000 ***
Herfindahl Index	0.5569	0.0237	23.524	0.0000 ***
Total Energy Market Share	1.3438	0.0336	39.955	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7483
Sensitivity	0.9578
Specificity	0.1250
Balanced Accuracy	0.5414

Diagnostics

McFadden's R^2	0.5706
AIC	63671
Total Observations	65390

Table A.8: **Pooled Firms (Model I):** The logit regression model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for pooled firms (Model I). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.5749	0.02395	-65.747	0.0000 ***
Log Assets	0.0371	0.0135	2.743	0.0061 **
Dummy Energy	-0.1499	0.0304	-4.924	0.0000 ***
Equity	-0.3509	0.0583	-6.025	0.0000 ***
Log Price	0.0515	0.0128	4.034	0.0001 ***
Net Income	-0.2452	0.0397	-6.181	0.0000 ***
Liabilities	-0.3965	0.1807	-2.194	0.0282 *
Revenue	-0.4484	0.0525	-8.534	0.0000 ***
Equity/Assets	-0.0054	0.0088	-0.616	0.5377
ROA	0.0101	0.0109	0.931	0.3517
ROE	0.0062	0.0132	0.468	0.6397
Div/Share	-0.8250	0.2317	-3.561	0.0004 ***
ESG Combined Score	-0.3433	0.0113	-30.345	0.0000 ***
Capital Expenditure	0.0212	0.0401	0.528	0.5972
Long Term Debt	-0.8104	0.4659	-1.739	0.0820 *
GDP Growth (annual %)	-0.2639	0.0221	-11.970	0.0000 ***
Log Inflation	0.1295	0.0249	5.209	0.0000 ***
Log oil prices	-0.4695	0.0421	-11.153	0.0000 ***
IFI	0.1200	0.0263	4.565	0.0000 ***
Log Uranium	0.2332	0.0394	5.911	0.0000 ***
Herfindahl Index	-0.6749	0.0692	-9.748	0.0000 ***
Total Energy Market Share	0.5196	0.0490	10.596	0.0000 ***
CO2	1.2341	0.0597	20.675	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7616
Sensitivity	0.9613
Specificity	0.1674
Balanced Accuracy	0.5644

Diagnostics

Adjusted R2 (McFadden R2)	0.5769
AIC	63,127
Total Observations	65,411

Table A.9: **Pooled Firms (Model II):** The logit regression model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. Additionally, we added the interaction term *energy dummy* (Model II). The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for pooled firms (Model I). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.5304	0.0231	-66.188	0.0000 ***
Log Assets	0.0854	0.0149	5.727	0.0000 ***
Dummy Energy	-1.5546	0.1633	-9.517	0.0000 ***
Equity	-0.3982	0.0752	-5.293	0.0000 ***
Log Price	0.0417	0.0132	3.155	0.0016 **
Net Income	-0.3173	0.0504	-6.292	0.0000 ***
Liabilities	-0.2521	0.1606	-1.569	0.1166
Revenue	-0.3326	0.0563	-5.904	0.0000 ***
Equity/Assets	-0.0167	0.0103	-1.631	0.1028
ROA	0.0213	0.0164	1.294	0.1958
ROE	0.0037	0.0115	0.318	0.7502
Div/Share	-0.3863	0.1786	-2.163	0.0305 *
ESG Combined Score	-0.4104	0.0126	-32.578	0.0000 ***
Capital Expenditure	0.0177	0.0458	0.387	0.6984
Long Term Debt	-0.4474	0.4395	-1.018	0.3087
GDP Growth (annual %)	-0.2669	0.0236	-11.305	0.0000 ***
Log Inflation	0.1281	0.0271	4.732	0.0000 ***
Log oil prices	-0.4675	0.0458	-10.217	0.0000 ***
IFI	0.1063	0.0282	3.768	0.0002 **
Herfindahl Index	-0.6563	0.0729	-8.998	0.0000 ***
Total Energy Market Share	0.5290	0.0530	9.982	0.0000 ***
Log Uranium	0.2402	0.0430	5.591	0.0000 ***
CO2	1.2262	0.0634	19.353	0.0000 ***
Dummy Energy: Log Uranium	-0.0455	0.1109	-0.410	0.6815
Dummy Energy: Log Assets	-0.1784	0.0394	-4.526	0.0000 ***
Dummy Energy: Equity	-0.0908	0.1972	-0.461	0.6451
Dummy Energy: Log Price	0.0706	0.0522	1.352	0.1765
Dummy Energy: Net Income	0.0391	0.1003	0.389	0.6970
Dummy Energy: Liabilities	-30.3534	2.8929	-10.492	0.0000 ***
Dummy Energy: Revenue	0.5758	0.1661	3.466	0.0005 ***
Dummy Energy: Equity/Assets	0.1012	0.0595	1.702	0.0888 .
Dummy Energy: ROA	-0.0677	0.0403	-1.679	0.0931 .
Dummy Energy: ROE	0.2365	0.3021	0.783	0.4337
Dummy Energy: Div/Share	-6.5083	3.0008	-2.169	0.0301 *
Dummy Energy: ESG Combined Score	0.3835	0.0293	13.073	0.0000 ***
Dummy Energy: Capital Expenditure	0.6460	0.1019	6.339	0.0000 ***
Dummy Energy: Long Term Debt	25.3646	3.1111	8.153	0.0000 ***
Dummy Energy: GDP Growth (annual %)	-0.0015	0.0689	-0.022	0.9827
Dummy Energy: Log Inflation	0.0185	0.0702	0.264	0.7921
Dummy Energy: Log oil prices	-0.0469	0.1193	-0.393	0.6943
Dummy Energy: IFI	0.1296	0.0817	1.586	0.1127
Dummy Energy: Herfindahl Index	-0.2422	0.2461	-0.984	0.3250
Dummy Energy: Total Energy Market Share	-0.0396	0.1456	-0.272	0.7856
Dummy Energy: CO2	0.1709	0.2036	0.839	0.4012
Confusion Matrix and Statistics				
Accuracy	0.7664			
Sensitivity	0.9510			
Specificity	0.2173			
Balanced Accuracy	0.5842			
Diagnostics				

Table A.10: **Energy Firms (Model III):** The logit regression model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for U.S. energy firms (Model III). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-2.4242	0.1696	-14.291	0.0000 ***
Log Assets	-0.0694	0.0384	-1.805	0.0711 *
Equity	-0.6250	0.2476	-2.524	0.0116 *
Log Price	0.0893	0.0330	2.705	0.0068 **
Net Income	-0.3081	0.1066	-2.890	0.0039 **
Liabilities	-5.4816	0.4923	-11.134	0.0000 ***
Revenue	0.4390	0.2266	1.937	0.0527 *
Equity/Assets	0.0182	0.0401	0.454	0.6499
ROA	-0.0222	0.0430	-0.515	0.6066
ROE	-0.0192	0.0346	-0.556	0.5786
Div/Share	-6.8726	2.9609	-2.321	0.0203 *
ESG Combined Score	-0.0491	0.0290	-1.693	0.0905 *
Capital Expenditure	1.1448	0.1587	7.215	0.0000 ***
Long Term Debt	2.2265	0.2556	8.712	0.0000 ***
GDP Growth (annual %)	-0.2269	0.0594	-3.822	0.0001 ***
Log Inflation	0.1480	0.0648	2.282	0.0225 *
Log oil prices	-0.4925	0.1100	-4.476	0.0000 ***
IFI	0.1575	0.0719	2.192	0.0284 *
Log Uranium	0.2439	0.1032	2.364	0.0181 *
Herfindahl Index	-0.6768	0.1932	-3.503	0.0005 ***
Total Energy Market Share	0.5227	0.1291	4.050	0.0001 ***
CO2	1.1999	0.1645	7.292	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7677
Sensitivity	0.9696
Specificity	0.1216
Balanced Accuracy	0.5456

Diagnostics

Adjusted R2 (McFadden R2)	0.5758
AIC	9490.3
Total Observations	10367

Table A.11: **Non-Energy Firms (Model IV):** The logit regression model based on firm specific variables, macroeconomic variables, and environmental variables. The table reports the β sensitivities and the standard errors in parentheses from the logit model, estimated for U.S. non-energy firms (Model IV). The selection of conditioning factors is based on a forward-and-backward algorithm on the basis of the McFadden R^2 and overall goodness-of-fit according with the Akaike Information Criterion (AIC). We perform the confusion matrix for all the previous logistic regressions in order to evaluate the performance of the model in classifying binary outcomes. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**z value**	$Pr(>\|z\|)$
(Intercept)	-1.5294	0.0244	-62.730	0.0000 ***
Log Assets	0.0909	0.0148	6.153	0.0000 ***
Equity	-0.3404	0.0685	-4.971	0.0000 ***
Log Price	0.0332	0.0131	2.538	0.0111 *
Net Income	-0.2846	0.0478	-5.957	0.0000 ***
Liabilities	-0.3323	0.1825	-1.820	0.0687 *
Revenue	-0.3109	0.0512	-6.073	0.0000 ***
Equity/Assets	-0.0216	0.0112	-1.934	0.0531 *
ROA	0.0237	0.0171	1.381	0.1674
ROE	0.0015	0.0101	0.151	0.8804
Div/Share	-0.1009	0.0574	-1.758	0.0787 *
ESG Combined Score	-0.4049	0.0124	-32.549	0.0000 ***
Capital Expenditure	0.0384	0.0330	1.164	0.2445
Long Term Debt	-0.6091	0.4661	-1.307	0.1913
GDP Growth (annual %)	-0.2878	0.0235	-12.256	0.0000 ***
Log Inflation	0.1291	0.0271	4.767	0.0000 ***
Log oil prices	-0.4535	0.0458	-9.900	0.0000 ***
IFI	0.0979	0.0281	3.489	0.0005 **
Log Uranium	0.2205	0.0429	5.134	0.0000 ***
Herfindahl Index	-0.6826	0.0724	-9.432	0.0000 ***
Total Energy Market Share	0.4899	0.0528	9.278	0.0000 ***
CO2	1.2509	0.0629	19.882	0.0000 ***

Confusion Matrix and Statistics

Metric	**Value**
Accuracy	0.7622
Sensitivity	0.9490
Specificity	0.2275
Balanced Accuracy	0.5882

Diagnostics

McFadden's R2	0.5972
AIC	53283
Total Observations	54969

Table A.12: **Cox Survival Model (Model I):** The table presents the results of the Cox proportional hazards model based on firm-specific variables. The coefficients (B) and standard errors (in parentheses) are reported for pooled energy and non-energy firms. The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The LR test ($\theta = 0$) tests the null hypothesis that latent factors or shared frailty are insignificant; this hypothesis is not rejected for the pooled firms, so the baseline Cox model without shared frailty is reported. The Wald test ($\beta = 0$) assesses the joint significance of all variables, while the Score (log-rank) test evaluates whether there is a statistically significant difference in survival times between the pooled firms. The results indicate significant differences in the survival experiences of energy and non-energy firms. The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\lvert z\rvert)$	**CI 95%**
Log Assets	0.0482	1.0494	0.0086	5.583	0.0000 ***	[1.0318, 1.0673]
Dummy Energy	-0.0055	0.9946	0.0207	-0.264	0.7921	[0.9550, 1.0358]
Equity	-0.0750	0.9278	0.0416	-1.805	0.0711 *	[0.8552, 1.0065]
Log Price	-0.0687	0.9336	0.0086	-7.992	0.0000 ***	[0.9180, 0.9495]
Net Income	0.1192	1.1266	0.0347	3.435	0.0006 ***	[1.0525, 1.2059]
Liabilities	-0.1127	0.8935	0.1073	-1.050	0.2938	[0.7240, 1.1026]
Revenue	0.1791	1.1961	0.0256	7.006	0.0000 ***	[1.1377, 1.2576]
Equity/Assets	-0.0028	0.9972	0.0099	-0.278	0.7810	[0.9780, 1.0168]
ROA	0.0033	1.0033	0.0137	0.239	0.8108	[0.9767, 1.0306]
ROE	-0.0245	0.9758	0.0168	-1.455	0.1456	[0.9441, 1.0085]
Div/Share	-0.0509	0.9503	0.0535	-0.953	0.3408	[0.8558, 1.0553]
ESG Combined Score	-0.0998	0.9050	0.0077	-12.951	0.0000 ***	[0.8915, 0.9188]
Long Term Debt	-0.8146	0.4428	0.2769	-2.942	0.0033 **	[0.2574, 0.7619]

Diagnostics

Concordance	0.539 (se = 0.002)
Likelihood ratio test	333.8 on 13 df, $p < 0.0000 * **$
Wald test	344.1 on 13 df, $p < 0.0000 * **$
Score (logrank) test	344.1 on 13 df, $p < 0.0000 * **$
AIC	371550.6
BIC	371653.8
Pseudo-R^2 (Harrell's C-index)	0.5001

Table A.13: **Cox Survival Model (Model II):** The table presents the results of the Cox proportional hazards model based on firm-specific variables and macroeconomic variables. The coefficients (B) and standard errors (in parentheses) are reported for pooled energy and non-energy firms. The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The LR test ($\theta = 0$) tests the null hypothesis that latent factors or shared frailty are insignificant; this hypothesis is not rejected for the pooled firms, so the baseline Cox model without shared frailty is reported. The Wald test ($\beta = 0$) assesses the joint significance of all variables, while the Score (log-rank) test evaluates whether there is a statistically significant difference in survival times between the pooled firms. The results indicate significant differences in the survival experiences of energy and non-energy firms. The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\|z\|)$	**CI 95%**
Log Assets	0.0803	1.0836	0.0085	9.413	0.0000 ***	[1.0656, 1.1019]
Dummy Energy	-0.0156	0.9845	0.0207	-0.754	0.4507	[0.9454, 1.0252]
Equity	-0.0434	0.9576	0.0411	-1.055	0.2913	[0.8834, 1.0379]
Log Price	-0.0155	0.9846	0.0087	-1.795	0.0726 *	[0.9680, 1.0014]
Net Income	0.0718	1.0744	0.0351	2.044	0.0410 *	[1.0030, 1.1510]
Liabilities	0.0862	1.0900	0.1047	0.823	0.4104	[0.8878, 1.3382]
Revenue	0.1498	1.1616	0.0263	5.686	0.0000 ***	[1.1032, 1.2232]
Equity/Assets	-0.0153	0.9848	0.0094	-1.622	0.1048	[0.9668, 1.0032]
ROA	0.0109	1.0109	0.0157	0.695	0.4873	[0.9804, 1.0424]
ROE	-0.0392	0.9616	0.0176	-2.227	0.0260 *	[0.9289, 0.9953]
Div/Share	-0.0965	0.9080	0.0588	-1.643	0.1005	[0.8092, 1.0188]
ESG Combined Score	-0.1357	0.8731	0.0077	-17.558	0.0000 ***	[0.8600, 0.8865]
Long Term Debt	-1.0517	0.3493	0.2832	-3.714	0.0002 ***	[0.2006, 0.6085]
GDP Growth (annual %)	0.0015	1.0015	0.0101	0.144	0.8858	[0.9818, 1.0215]
Log Inflation	-0.1522	0.8588	0.0082	-18.550	0.0000 ***	[0.8451, 0.8727]
Log Oil Prices	0.3115	1.3655	0.0118	26.319	0.0000 ***	[1.3342, 1.3976]
IFI	0.2746	1.3160	0.0154	17.808	0.0000 ***	[1.2768, 1.3563]
Log Uranium	0.0317	1.0322	0.0141	2.252	0.0243 *	[1.0041, 1.0611]
Diagnostics						
Concordance	0.673 (se = 0.002)					
Likelihood ratio test	4002 on 18 df, $p < 0.0000***$					
Wald test	3750 on 18 df, $p < 0.0000***$					
Score (logrank) test	3890 on 18 df, $p < 0.0000***$					
AIC	443332.7					
BIC	443478.6					
Pseudo-R^2 (Harrell's C-index)	0.5089					

Table A.14: **Cox Survival Model (Model II):** The table presents the results of the Cox proportional hazards model based on firm-specific variables, macroeconomic variables and energy market structure variables. The coefficients (B) and standard errors (in parentheses) are reported for pooled energy and non-energy firms. The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The LR test ($\theta = 0$) tests the null hypothesis that latent factors or shared frailty are insignificant; this hypothesis is not rejected for the pooled firms, so the baseline Cox model without shared frailty is reported. The Wald test ($\beta = 0$) assesses the joint significance of all variables, while the Score (log-rank) test evaluates whether there is a statistically significant difference in survival times between the pooled firms. The results indicate significant differences in the survival experiences of energy and non-energy firms. The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\|z\|)$	**CI 95%**
lassets	0.0894	1.0935	0.0093	9.583	0.0000 ***	[1.0737, 1.1137]
Equity	0.0045	1.0045	0.0416	0.109	0.9130	[0.9260, 1.0898]
lprice	-0.0029	0.9971	0.0089	-0.329	0.7419	[0.9799, 1.0146]
Net Income	0.0736	1.0764	0.0361	2.042	0.0412 *	[1.0030, 1.1553]
Liabilities	0.0486	1.0498	0.1370	0.355	0.7226	[0.8027, 1.3730]
Revenue	0.1648	1.1792	0.0313	5.264	0.0000 ***	[1.1090, 1.2538]
Equity/Assets	-0.0201	0.9801	0.0101	-1.983	0.0473 *	[0.9609, 0.9998]
ROA	0.0189	1.0191	0.0178	1.064	0.2872	[0.9842, 1.0552]
ROE	-0.0350	0.9656	0.0173	-2.024	0.0429 *	[0.9334, 0.9989]
Div/Share	-0.1178	0.8889	0.0628	-1.876	0.0606 *	[0.7859, 1.0053]
ESG Combined Score	-0.1305	0.8777	0.0082	-15.832	0.0000 ***	[0.8636, 0.8920]
Capital Expenditure	-0.00007	0.9999	0.00002	-3.641	0.0003 ***	[0.9999, 1.0000]
Long Term Debt	-0.2965	0.7434	0.3826	-0.775	0.4385	[0.3512, 1.5738]
GDP Growth (annual %)	0.0354	1.0360	0.0133	2.660	0.0078 **	[1.0094, 1.0633]
Log Inflation	0.1398	1.1500	0.0169	8.277	0.0000 ***	[1.1126, 1.1887]
Log Oil Prices	-0.2620	0.7695	0.0306	-8.558	0.0000 ***	[0.7247, 0.8171]
Log Uranium	0.2322	1.2614	0.0281	8.274	0.0000 ***	[1.1939, 1.3327]
IFI	0.1272	1.1356	0.0182	6.992	0.0000 ***	[1.0958, 1.1768]
HerfindahlIndex	0.4337	1.5430	0.0190	22.868	0.0000 ***	[1.4867, 1.6015]
Total Market Share	0.5948	1.8127	0.0262	22.673	0.0000 ***	[1.7218, 1.9083]
Diagnostics						
Concordance				0.688 (se = 0.002)		
Likelihood ratio test				4099 on 20 df, $p < 0.0000***$		
Wald test				3890 on 20 df, $p < 0.0000***$		
Score (logrank) test				4121 on 20 df, $p < 0.0000***$		
AIC				367711.1		
BIC				367870		
Pseudo-R^2				0.5110		

Table A.15: **Cox Survival Model (Model II):** The table presents the results of the Cox proportional hazards model based on firm-specific variables, macroeconomic variables, energy market structure and environmental variables. The coefficients (B) and standard errors (in parentheses) are reported for pooled energy and non-energy firms. The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The LR test ($\theta = 0$) tests the null hypothesis that latent factors or shared frailty are insignificant; this hypothesis is not rejected for the pooled firms, so the baseline Cox model without shared frailty is reported. The Wald test ($\beta = 0$) assesses the joint significance of all variables, while the Score (log-rank) test evaluates whether there is a statistically significant difference in survival times between the pooled firms. The results indicate significant differences in the survival experiences of energy and non-energy firms. The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\lvert z\rvert)$	**95% CI**
Log Assets	0.0951	1.0997	0.0095	9.981	0.0000 ***	[1.0794, 1.1205]
Dummy Energy	-0.0156	0.9846	0.0218	-0.714	0.4755	[0.9434, 1.0275]
Equity	0.0054	1.0054	0.0418	0.128	0.8978	[0.9264, 1.0911]
Log Price	-0.0025	0.9975	0.0096	-0.265	0.7912	[0.9789, 1.0164]
Net Income	0.0645	1.0667	0.0361	1.788	0.0738 *	[0.9938, 1.1448]
Liabilities	0.0450	1.0460	0.1385	0.325	0.7451	[0.7974, 1.3721]
Revenue	0.1612	1.1750	0.0315	5.121	0.0000 ***	[1.1047, 1.2498]
Equity/Assets	-0.0194	0.9808	0.0102	-1.890	0.0587 *	[0.9613, 1.0007]
ROA	0.0178	1.0179	0.0181	0.981	0.3268	[0.9824, 1.0547]
ROE	-0.0346	0.9660	0.0171	-2.024	0.0430 *	[0.9341, 0.9989]
Div/Share	-0.1108	0.8951	0.0612	-1.812	0.0700 *	[0.7940, 1.0091]
ESG Combined Score	-0.1320	0.8763	0.0083	-16.001	0.0000 ***	[0.8623, 0.8906]
Capital Expenditure	-0.0001	0.9999	0.0000	-3.304	0.0009 ***	[0.9999, 1.0000]
Long Term Debt	-0.3537	0.7021	0.3839	-0.921	0.3569	[0.3308, 1.4899]
GDP Growth (annual %)	-0.1639	0.8488	0.0178	-9.220	0.0000 ***	[0.8197, 0.8789]
Log Inflation	0.0449	1.0459	0.0179	2.501	0.0124 *	[1.0098, 1.0834]
Log oil prices	-0.1901	0.8269	0.0311	-6.111	0.0000 ***	[0.7780, 0.8789]
Log Uranium	0.1105	1.1169	0.0288	3.836	0.0001 ***	[1.0555, 1.1817]
IFI	0.0574	1.0591	0.0216	2.655	0.0079 **	[1.0151, 1.1049]
Herfindahl Index	-0.3422	0.7102	0.0573	-5.974	0.0000 ***	[0.6348, 0.7946]
Total Energy Market Share	0.1843	1.2024	0.0362	5.090	0.0000 ***	[1.1200, 1.2908]
CO2	0.7415	2.0991	0.0478	15.526	0.0000 ***	[1.9115, 2.3051]
Diagnostics						
Concordance	0.693 (se = 0.002)					
Likelihood ratio test	4400 on 22 df, p = <0.0000 ***					
Wald test	4007 on 22 df, p = <0.0000 ***					
Score (logrank) test	4330 on 22 df, p = <0.0000 ***					
AIC	367414.1					
BIC	367588.8					
Pseudo-R^2	0.5118					

Table A.16: **Cox Survival Model (Model II):** The table presents the results of the Cox proportional hazards model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. Additionally, we added the interaction term *energy dummy* (Model II). The coefficients (B) and standard errors (in parentheses) are reported for pooled energy and non-energy firms. The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The LR test ($\theta = 0$) tests the null hypothesis that latent factors or shared frailty are insignificant; this hypothesis is not rejected for the pooled firms, so the baseline Cox model without shared frailty is reported. The Wald test ($\beta = 0$) assesses the joint significance of all variables, while the Score (log-rank) test evaluates whether there is a statistically significant difference in survival times between the pooled firms. The results indicate significant differences in the survival experiences of energy and non-energy firms. The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\|z\|)$	**CI 95%**
Log Assets	0.1114	1.1178	0.0106	10.540	0.0000 ***	[1.0915, 1.1441]
Dummy Energy	0.4469	1.5634	0.1443	3.097	0.001955 **	[1.1813, 1.9842]
Equity	-0.0478	0.9534	0.0455	-1.050	0.2939	[0.8625, 1.0533]
Log Price	0.0037	1.0037	0.0100	0.368	0.7125	[0.9835, 1.0244]
Log Uranium	0.1176	1.1248	0.0312	3.770	0.0002 **	[1.0543, 1.1992]
Net Income	0.1439	1.1547	0.0391	3.678	0.0002 **	[1.0677, 1.2484]
Liabilities	0.0971	1.1019	0.1455	0.668	0.5044	[0.8224, 1.4125]
Revenue	0.1682	1.1831	0.0341	4.928	0.0000 ***	[1.1030, 1.2725]
Equity/Assets	-0.0243	0.9760	0.0151	-1.604	0.1086	[0.9493, 1.0035]
ROA	0.0280	1.0284	0.0306	0.916	0.3598	[0.9672, 1.0912]
ROE	-0.0374	0.9632	0.0176	-2.130	0.0332 *	[0.9283, 0.9990]
Div/Share	-0.1078	0.8978	0.0609	-1.771	0.0766 *	[0.7827, 1.0156]
ESG Combined Score	-0.1631	0.8495	0.0091	-17.866	0.0000 ***	[0.8317, 0.8673]
Capital Expenditure	-0.00006	0.99994	0.00002	-2.434	0.0149 *	[0.9998, 1.000]
Long Term Debt	-0.8513	0.4269	0.4101	-2.076	0.0379 *	[0.2105, 0.8810]
CO2	0.7439	2.1040	0.0506	14.715	0.0000 ***	[2.0044, 2.2202]
Herfindahl Index	-0.3318	0.7177	0.0603	-5.503	0.0000 ***	[0.6062, 0.8726]
Total Market Share	0.2007	1.2223	0.0390	5.150	0.0000 ***	[1.1230, 1.3345]
GDP Growth (annual %)	-0.1675	0.8457	0.0189	-8.841	0.0000 ***	[0.8098, 0.8826]
Log Inflation	0.0488	1.0500	0.0194	2.512	0.0120 *	[1.0103, 1.0903]
Log oil prices	-0.1971	0.8211	0.0336	-5.859	0.0000 ***	[0.7558, 0.8912]
IFI	0.0580	1.0597	0.0230	2.520	0.0117 *	[1.0121, 1.1074]
Dummy Energy: Capital Expenditure	0.9999	1.0001	0.00005	5.2690	0.0000 ***	[0.9997, 1.000]
Dummy Energy: Long Term Debt	160.0558	0.006248	1.7417	4861.9970	0.0036 **	[123.43, 215.17]
Dummy Energy: Log Uranium	0.9791	1.0213	0.0818	-0.258	0.7965	[0.8231, 1.1342]
Dummy Energy: Equity	1.3158	0.7599	0.9479	1.8264	0.0756 *	[0.88241, 1.8264]
Dummy Energy: Log Price	0.9614	1.0401	0.8935	0.034	0.8389	[0.89350, 1.0345]
Dummy Energy: Net Income	0.7071	1.4142	0.6015	0.8314	0.1112	[0.60145, 1.0224]
Dummy Energy: Liabilities	4.0545	0.2466	0.10938	0.10938	0.0379 *	[0.2105, 1.3456]
Dummy Energy: Revenue	0.8791	1.1375	0.6741	1.1465	0.0903 *	[0.67411, 1.1465]
Dummy Energy: Equity/Assets	1.0007	0.9993	0.93856	1.0669	0.0954 *	[0.9761, 1.0224]
Dummy Energy: ROA	0.9890	1.0111	0.9191	1.0641	0.0892 *	[0.9672, 1.0234]
Dummy Energy: ROE	0.9876	1.0125	0.6042	1.6145	0.0604 *	[0.9283, 1.0762]
Dummy Energy: Div/Share	2.2164	0.4512	0.0137	358.4389	0.0001 ***	[1.12715, 1.2270]
Dummy Energy: ESG Combined Score	1.1760	0.8503	1.12715	0.4512	0.0001 ***	[1.1271, 1.2270]
Dummy Energy: GDP Growth (annual %)	1.0303	0.9706	0.92297	1.1501	0.0382 *	[0.92297, 1.1501]
Dummy Energy: Log Inflation	0.9925	1.0075	0.89805	1.0970	0.0893 *	[0.8884, 1.1170]
Dummy Energy: Log oil prices	1.0458	0.9561	0.87882	1.2446	0.0542 *	[0.9553, 1.3452]
Dummy Energy: IFI	0.9795	1.0210	0.8527	1.1251	0.0921 *	[0.8540, 1.3470]
Dummy Energy: HerfindahlIndex	0.9613	1.0402	0.6448	1.4332	0.0784 *	[0.8233, 1.0223]
Dummy Energy: TotalMarketShare	0.9338	1.0709	0.7561	1.1531	0.0039 ***	[0.7563, 1.1531]
Dummy Energy: CO2	0.9780	1.0225	0.7097	1.3478	0.0923 *	[0.9123, 1.3901]
			Diagnostics			
Concordance	0.686		(se = 0.002)			
Likelihood ratio test	3807		on 43 df, p = <0.0000 ***			
Wald test	801.4		on 43 df, p = <0.0000 ***			
Score (logrank) test	3818		on 43 df, p = <0.0000 ***			
AIC	362207.3					
BIC	362548.2					
Pseudo-R^2	0.5819					

Table A.17: **Cox Survival Model (Model III):** The table presents the results of the Cox proportional hazards model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. The coefficients (B) and standard errors (in parentheses) are reported for U.S. energy firms (Model III). The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\|z\|)$	**CI 95%**
Log Assets	0.0467	1.0478	0.0283	1.653	0.0983 *	[0.9914, 1.1075]
Equity	0.3283	1.3887	0.2228	1.474	0.1406	[0.8973, 2.1490]
Log Price	-0.0229	0.9774	0.0235	-0.974	0.3302	[0.9335, 1.0234]
Net Income	-0.2684	0.7646	0.0956	-2.808	0.00498 **	[0.6340, 0.9221]
Liabilities	0.2564	1.2923	0.3018	0.850	0.3955	[0.7152, 2.3350]
Revenue	0.0749	1.0778	0.1908	0.392	0.6948	[0.7415, 1.5666]
Equity/Assets	-0.0348	0.9658	0.0433	-0.804	0.4214	[0.8872, 1.0513]
ROA	0.0126	1.0126	0.0156	0.807	0.4198	[0.9822, 1.0441]
ROE	-0.0086	0.9914	0.0250	-0.344	0.7312	[0.9439, 1.0413]
Div/Share	1.0740	2.9270	2.5919	0.414	0.6786	[0.0182, 470.64]
ESG Combined Score	0.0019	1.0019	0.0213	0.091	0.9276	[0.9609, 1.0448]
Capital Expenditure	-0.0002	0.9998	0.000049	-4.583	0.000004576 ***	[0.9997, 0.9999]
Long Term Debt	0.3884	1.4747	0.1348	2.881	0.00396 **	[1.1322, 1.9207]
GDP Growth (annual %)	-0.1415	0.8680	0.0508	-2.784	0.00537 **	[0.7857, 0.9590]
Log Inflation	0.0436	1.0446	0.0474	0.920	0.3575	[0.9519, 1.1462]
Log oil prices	-0.1621	0.8503	0.0823	-1.969	0.0489 *	[0.7236, 0.9993]
Log Uranium	0.1051	1.1108	0.0761	1.380	0.1676	[0.9568, 1.2895]
IFI	0.0315	1.0320	0.0660	0.477	0.6332	[0.9068, 1.1746]
Herfindahl Index	-0.3804	0.6836	0.1904	-1.998	0.0457 *	[0.4707, 0.9928]
Total Energy Market Share	0.1427	1.1534	0.0993	1.437	0.1507	[0.9494, 1.4013]
CO2	0.7506	2.1182	0.1533	4.896	0.000000978 ***	[1.5685, 2.8606]
Diagnostics						
Concordance					0.677 (se = 0.005)	
Likelihood ratio test					521.6 on 21 df, p = <0.0000 ***	
Wald test					472.4 on 21 df, p = <0.0000 ***	
Score (logrank) test					502.4 on 21 df, p = <0.0000 ***	
AIC					43494.75	
BIC					43621.71	
Pseudo-R^2 (Harrell's C-index)					0.5119	

Table A.18: **Cox Survival Model (Model IV):** The table presents the results of the Cox proportional hazards model based on firm specific variables, macroeconomic variables, energy market structure and environmental variables. The coefficients (B) and standard errors (in parentheses) are reported for U.S. non-energy firms (Model III). The Exp(coef.) represents the hazard ratios as predicted by the model. Variables were selected using a forward-and-backward algorithm based on individual significance (LR tests) and overall goodness-of-fit (AIC). The BIC represents the Bayesian Information Criterion, and the Pseudo-R^2 is the McFadden goodness-of-fit criterion. *, **, *** denote significance at the 10%, 5%, and 1% levels, respectively.

Variable	**Coef**	**exp(Coef)**	**se(Coef)**	**z value**	$Pr(>\|z\|)$	**CI 95%**
Log Assets	0.1082	1.1143	0.0104	10.364	<0.0000 ***	[1.0917, 1.1374]
Equity	-0.0439	0.9571	0.0422	-1.040	0.2985	[0.8810, 1.0396]
Log Price	0.0036	1.0036	0.0099	0.361	0.7179	[0.9843, 1.0233]
Net Income	0.1352	1.1448	0.0369	3.665	0.0002 ***	[1.0649, 1.2306]
Liabilities	0.1037	1.1092	0.1557	0.666	0.5055	[0.8175, 1.5050]
Revenue	0.1490	1.1607	0.0310	4.811	0.0000 ***	[1.0923, 1.2333]
Equity/Assets	-0.0212	0.9790	0.0135	-1.571	0.1162	[0.9534, 1.0053]
ROA	0.0284	1.0288	0.0315	0.900	0.3679	[0.9672, 1.0943]
ROE	-0.0393	0.9615	0.0189	-2.079	0.0376 *	[0.9265, 0.9978]
Div/Share	-0.1063	0.8991	0.0607	-1.751	0.0799 *	[0.7982, 1.0128]
ESG Combined Score	-0.1583	0.8536	0.0090	-17.628	<0.0000 ***	[0.8387, 0.8688]
Capital Expenditure	-0.0001	0.9999	0.0000	-2.328	0.0199 *	[0.9999, 1.0000]
Long Term Debt	-0.8875	0.4117	0.4409	-2.013	0.0441 *	[0.1735, 0.9769]
GDP Growth (annual %)	-0.1667	0.8465	0.0191	-8.746	<0.0000 ***	[0.8154, 0.8787]
Log Inflation	0.0490	1.0502	0.0194	2.524	0.0116 *	[1.0110, 1.0910]
Log oil prices	-0.1961	0.8220	0.0336	-5.829	<0.0000 ***	[0.7695, 0.8780]
Log Uranium	0.1167	1.1238	0.0312	3.745	0.0002 ***	[1.0572, 1.1946]
IFI	0.0589	1.0607	0.0231	2.557	0.0106 *	[1.0138, 1.1097]
Herfindahl Index	-0.3296	0.7192	0.0604	-5.456	<0.0000 ***	[0.6389, 0.8096]
Total Energy Market Share	0.1995	1.2208	0.0390	5.112	0.00000031913 ***	[1.1309, 1.3178]
CO2	0.7381	2.0919	0.0506	14.583	<0.0000 ***	[1.8943, 2.3100]
Diagnostics						
Concordance					0.689 (se = 0.002)	
Likelihood ratio test					3960 on 21 df, p = <0.0000 ***	
Wald test					3628 on 21 df, p = <0.0000 ***	
Score (logrank) test					3921 on 21 df, p = <0.0000 ***	
AIC					306306.9	
BIC					306470.3	
Pseudo-R^2 (Harrell's C-index)					0.5128	

Table A.19: **Z-score OLS regression (Model A)**. The table reports the results from the OLS estimation with the z-score (dependent variable) inspired by the Altman z-score formula. The z-sore model based on income statement variables, macroeconomic and market structure, and environmental variables. The table reports the B sensitivities and the p-values in parentheses from the z-score model, estimated for the U.S pooled firms (Model A). The Pseudo-R2 is the McFadden goodness-of-fit criteria. Standard errors are reported for the z-score OLS estimations. The p-values are in square brackets. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**t value**	$Pr(>\|t\|)$	**Significance**
(Intercept)	-62.2700	8.4170	-7.40	0.0000	***
Log Assets	234.6340	9.8450	23.83	<0.0000	***
Dummy Energy	-77.7240	23.0360	-3.37	0.0007	***
Equity	-38.9000	17.3780	-2.24	0.0252	*
Log Price	-29.7060	9.1440	-3.25	0.0012	**
Net Income	3.2720	9.9480	0.33	0.7422	
Liabilities	-30.6250	24.6510	-1.24	0.2141	
Revenue	-21.3350	12.2680	-1.74	0.0820	*
Equity/Assets	1133.6370	7.2010	157.42	<0.0000	***
ROA	166.3050	7.1890	23.13	<0.0000	***
ROE	-10.9910	6.9730	-1.58	0.1150	
Div/Share	-3.5630	8.2060	-0.43	0.6642	
ESG Combined Score	-39.4070	8.2440	-4.78	0.0000	***
Capital Expenditure	-2.2590	13.1330	-0.17	0.8634	
Long Term Debt	-3.9620	26.6640	-0.15	0.8819	
GDP Growth (annual %)	-0.7680	13.5540	-0.06	0.9548	
Log Inflation	1.1700	20.3100	0.06	0.9541	
Log oil prices	-3.6580	34.1570	-0.11	0.9147	
Log Uranium	-6.0200	32.8110	-0.18	0.8544	
IFI	-0.3390	18.0300	-0.02	0.9850	
Herfindahl Index	-10.8230	29.5000	-0.37	0.7137	
Total Energy Market Share	10.9020	33.2580	0.33	0.7431	
CO2	33.9890	31.5640	1.08	0.2816	

Diagnostics

Residual standard error	2150 on 81546 degrees of freedom
Multiple R-squared	0.574
Adjusted R-squared	0.573
F-statistic	1.4e+03 on 22 and 81546 DF, p-value: <0.0000
AIC	1483421
BIC	1483644

Table A.20: **Z-score OLS regression (Model B)**. The table reports the results from the OLS estimation with the z-score (dependent variable) inspired by the Altman z-score formula. The z-sore model based on income statement variables, macroeconomic and market structure, and environmental variables. The table reports the B sensitivities and the p-values in parentheses from the z-score model, estimated for the U.S energy firms for surviving and failed firms (Model B). The Pseudo-R2 is the McFadden goodness-of-fit criteria. Standard errors are reported for the z-score OLS estimations. The p-values are in square brackets. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**t value**	$Pr(>\lvert t \rvert)$	**Significance**
(Intercept)	-146.0100	54.9300	-2.66	0.0079	**
Log Assets	165.3900	34.6600	4.77	<0.0000	***
Equity	14.0400	49.2500	0.29	0.7756	
Log Price	-37.7000	50.4200	-0.75	0.4546	
Net Income	-12.4100	27.8800	-0.45	0.6561	
Liabilities	-229.0100	579.9500	-0.39	0.6929	
Revenue	14.2200	43.5000	0.33	0.7437	
Equity/Assets	1578.5900	17.4600	90.40	<0.0000	***
ROA	237.3000	36.0900	6.57	<0.0000	***
ROE	878.1700	255.4800	3.44	0.0006	**
Div/Share	-4.4800	25.2200	-0.18	0.8591	
ESG Combined Score	-16.4700	25.3200	-0.65	0.5154	
Capital Expenditure	-15.3500	38.2600	-0.40	0.6883	
Long Term Debt	-294.7400	889.0500	-0.33	0.7403	
GDP Growth (annual %)	78.7500	46.5000	1.69	0.0904	*
Log Inflation	45.2700	67.5400	0.67	0.5027	
Log oil prices	-51.8900	113.7600	-0.46	0.6483	
Log Uranium	-20.3300	109.0200	-0.19	0.8521	
IFI	23.4200	61.7700	0.38	0.7046	
Herfindahl Index	108.1800	100.5800	1.08	0.2821	
Total Market Share	103.6000	111.9200	0.93	0.3547	
CO2	-7.4000	107.5100	-0.07	0.9451	
Diagnostics					
Residual standard error	2870 on 12810 degrees of freedom				
Multiple R-squared	0.523				
Adjusted R-squared	0.522				
F-statistic	448 on 21 and 12810 DF, p-value: <0.0000				
AIC	240736				
BIC	240907				

Table A.21: **Z-score OLS regression (Model C).** The table reports the results from the OLS estimation with the z-score (dependent variable) inspired by the Altman z-score formula. The z-sore model based on income statement variables, macroeconomic and market structure, and environmental variables. The table reports the B sensitivities and the p-values in parentheses from the z-score model, estimated for the U.S non-energy firms for surviving and failed firms (Model C). The Pseudo-R2 is the McFadden goodness-of-fit criteria. Standard errors are reported for the z-score OLS estimations. The p-values are in square brackets. *, **, *** denote significance at the 10%, 5% and 1% respectively.

Variable	**Estimate**	**Std. Error**	**t value**	$Pr(>\|t\|)$	**Significance**
(Intercept)	-61.14	7.69	-7.95	0.0000	***
Log Assets	259.21	9.98	25.98	<0.0000	***
Equity	-57.29	18.25	-3.14	0.0017	**
Log Price	-30.87	8.61	-3.59	0.0003	***
Net Income	5.63	10.57	0.53	0.5943	
Liabilities	-14.08	23.84	-0.59	0.5549	
Revenue	-31.30	12.74	-2.46	0.0140	*
Equity/Assets	929.89	7.88	117.99	<0.0000	***
ROA	187.68	6.81	27.56	<0.0000	***
ROE	-13.72	6.35	-2.16	0.0308	*
Div/Share	-2.51	8.30	-0.30	0.7619	
ESG Combined Score	-45.31	8.38	-5.41	0.0000	***
Capital Expenditure	2.07	14.52	0.14	0.8867	
Long Term Debt	-23.05	26.16	-0.88	0.3782	
GDP Growth (annual %)	-11.03	13.40	-0.82	0.4103	
Log Inflation	-10.32	20.18	-0.51	0.6092	
Log oil prices	8.86	33.93	0.26	0.7941	
Log Uranium	-8.40	32.61	-0.26	0.7966	
IFI	-2.65	17.82	-0.15	0.8817	
Herfindahl Index	-26.71	29.19	-0.92	0.3601	
Total Energy Market Share	-5.94	32.98	-0.18	0.8570	
CO2	36.23	31.24	1.16	0.2461	
Diagnostics					
Residual standard error	1960 on 68715 degrees of freedom				
Multiple R-squared	0.519				
Adjusted R-squared	0.518				
F-statistic	915 on 21 and 68715 DF, p-value: <0.0000				
AIC	1237140				
BIC	1237350				

Table A.22: **Average Predicted Probability of Corporate Failure for Energy Firms (2010-2022)**. Note: Utilizing the Fiedler value to inform the predictive model. This involves integrating network information with the logistic regression model.

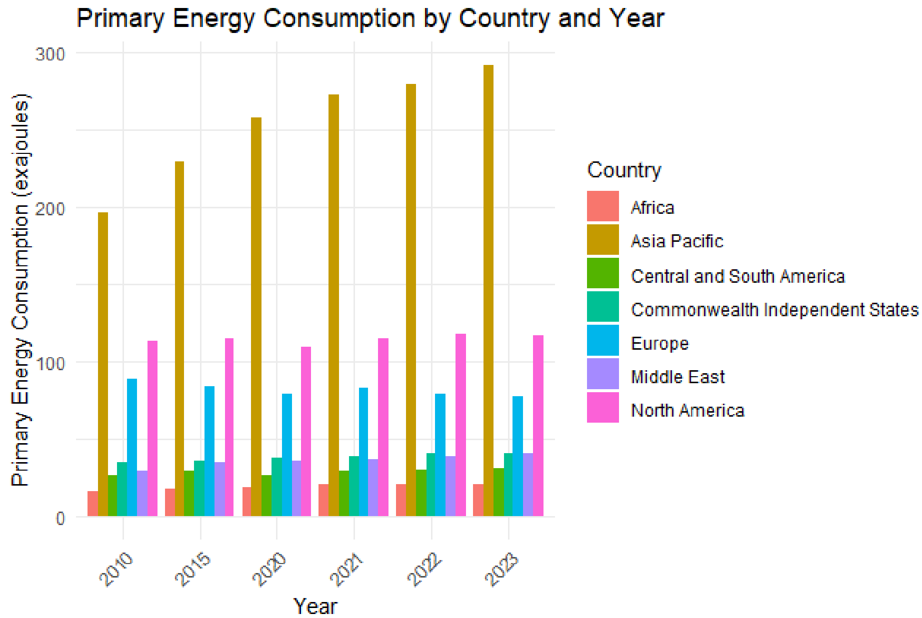
Year	Average Predicted Probability of Failure
2010	0.401
2011	0.424
2012	0.363
2013	0.355
2014	0.349
2015	0.285
2016	0.241
2017	0.209
2018	0.127
2019	0.128
2020	0.0701
2021	0.0413
2022	0.0040

Table A.23: **Average Predicted Probability of Corporate Failure for Non-Energy Firms (2010-2022)**. Note: Utilizing the Fiedler value to inform the predictive model. This involves integrating network information with the logistic regression model.

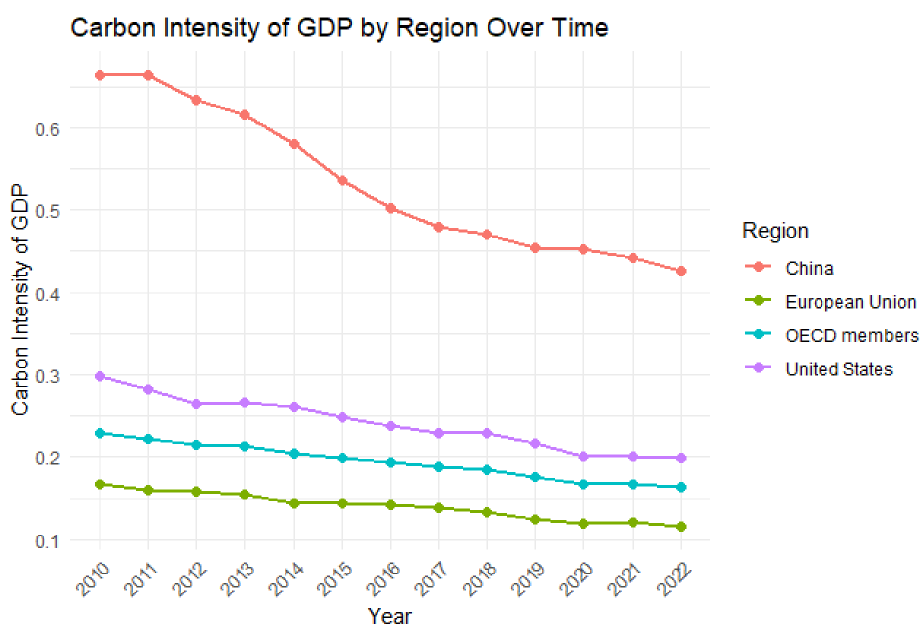
Year	Average Predicted Probability of Failure
2010	0.464
2011	0.415
2012	0.387
2013	0.400
2014	0.376
2015	0.289
2016	0.264
2017	0.207
2018	0.126
2019	0.145
2020	0.103
2021	0.0670
2022	0.0036

Table A.24: **Eigenvector Centrality for Energy and Non-Energy Firms (2010-2022)**. Note: Utilizing the Fiedler value to inform the predictive model. This involves integrating network information with the logistic regression model.

Year	**Non-Energy Firms**	**Energy Firms**
2010	0.601	0.515
2011	0.632	0.486
2012	0.693	0.451
2013	0.800	0.410
2014	0.746	0.482
2015	0.901	0.774
2016	0.818	0.706
2017	0.883	0.884
2018	0.990	0.948
2019	0.987	0.972
2020	0.990	0.919
2021	1.000	1.000
2022	1.000	1.000



(a) **Primary energy consumption worldwide from 2010 to 2023, by region (in exajoules)**. Source: Energy Institute June 2024, Statistical Review of World Energy 2024. Primary energy comprises commercially traded fuels only, including modern renewables used to generate electricity. This statistic was compiled using several releases of the publication.



(b) **Carbon intensity of GDP (kg CO2 emissions per 2021 PPP \$ of GDP), 2010-2022**. Source: EDGAR (Emissions Database for Global Atmospheric Research), (2023) European Commission, JRC (Datasets). Note: Annual emissions of carbon dioxide (CO2), one of the six Kyoto greenhouse gases (GHG), from the agriculture, energy, waste, and industrial sectors, excluding LULUCF divided by the GDP in 2021 PPP \$.

Figure A.1: **Energy Consumption and CO2 Emissions.**

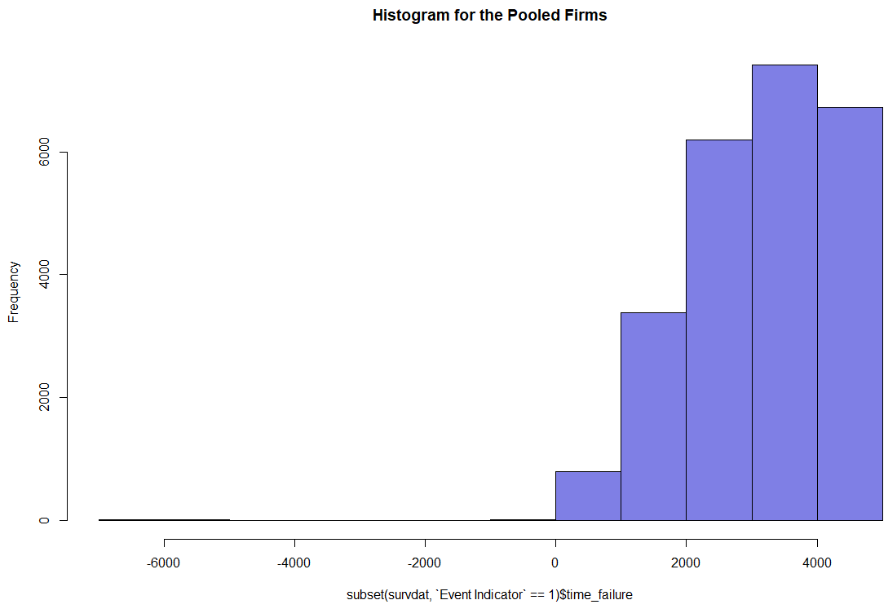


Figure A.2: **Histogram for both energy and non-energy U.S. firms that failed during the time period of 2010 to 2022.** Note: The x-axis represents the time to failure event, in this analysis the starting day 40237 corresponds to the fiscal year of 2010. The survival time is computed by subtracting the Research Company Deletion Date and 40237.

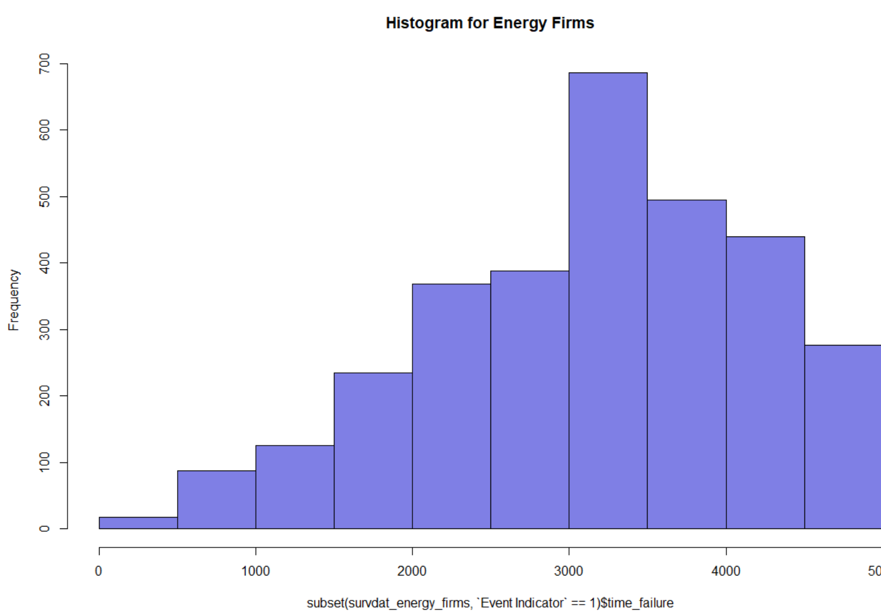


Figure A.3: **Histogram for energy U.S. firms that failed during the time period of 2010 to 2022.** Note: The x-axis represents the time to failure event, in this analysis the starting day 40237 corresponds to the fiscal year of 2010. The survival time is computed by subtracting the Research Company Deletion Date and 40237.

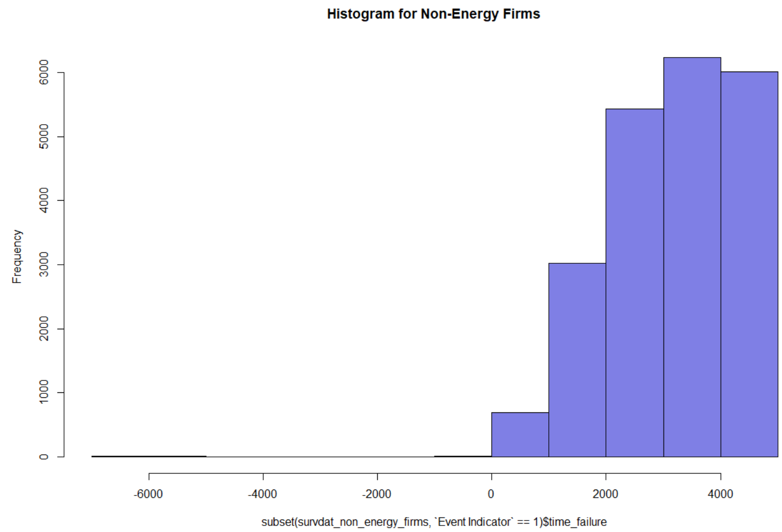


Figure A.4: **Histogram for non-energy U.S. firms that failed during the time period of 2010 to 2022.** Note: The x-axis represents the time to failure event, in this analysis the starting day 40237 corresponds to the fiscal year of 2010. The survival time is computed by subtracting the Research Company Deletion Date and 40237.

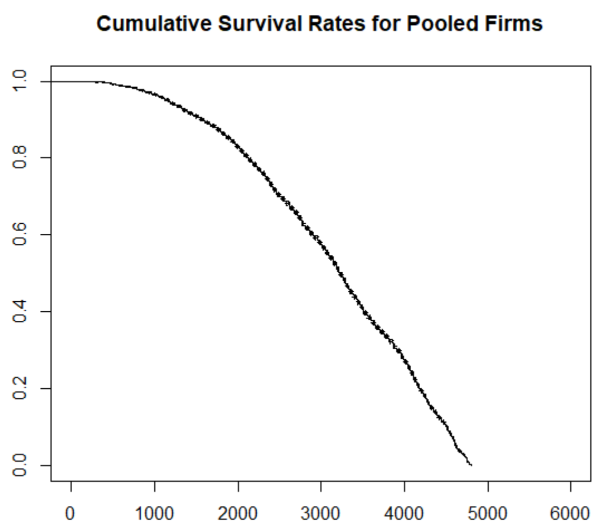


Figure A.5: **Kaplan-Meier survival curve for the Pooled Firms.** Note: The x-axis represents the time duration (in years after the starting date) of the study or observation period. The curve starts at time 0 and extends to the maximum observed time. The y-axis represents the cumulative survival probability or the proportion of the pooled firms that have survived up to a specific point in time.

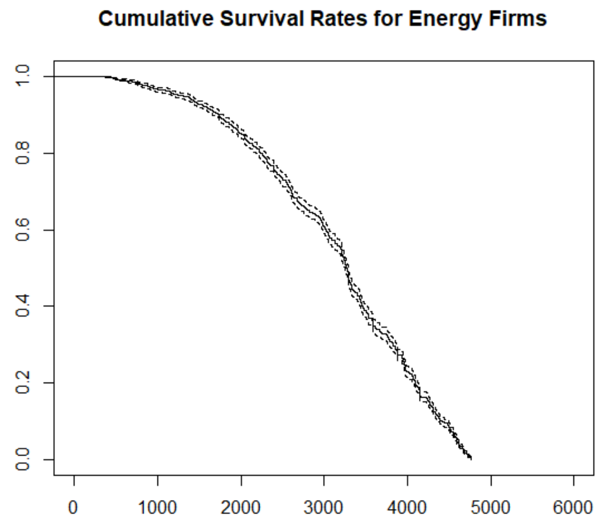


Figure A.6: **Kaplan-Meier survival curve for energy firms.** Note: The x-axis represents the time duration (in years after the starting date) of the study or observation period. The curve starts at time 0 and extends to the maximum observed time. The y-axis represents the cumulative survival probability or the proportion of the pooled firms that have survived up to a specific point in time.

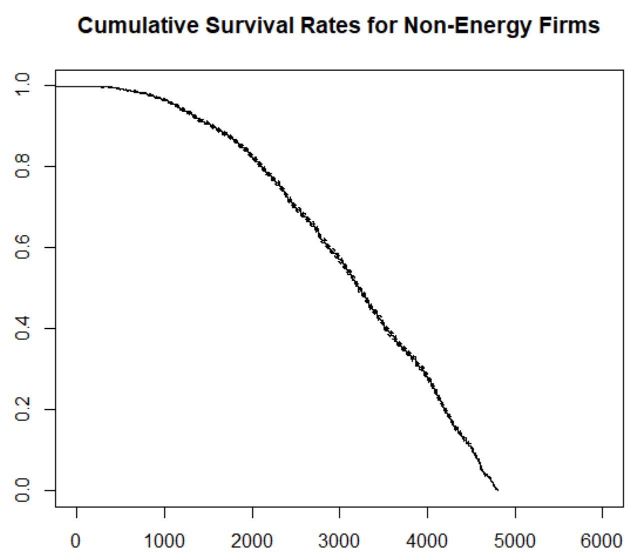


Figure A.7: **Kaplan-Meier survival curve for non-energy firms.** Note: The x-axis represents the time duration (in years after the starting date) of the study or observation period. The curve starts at time 0 and extends to the maximum observed time. The y-axis represents the cumulative survival probability or the proportion of the pooled firms that have survived up to a specific point in time.

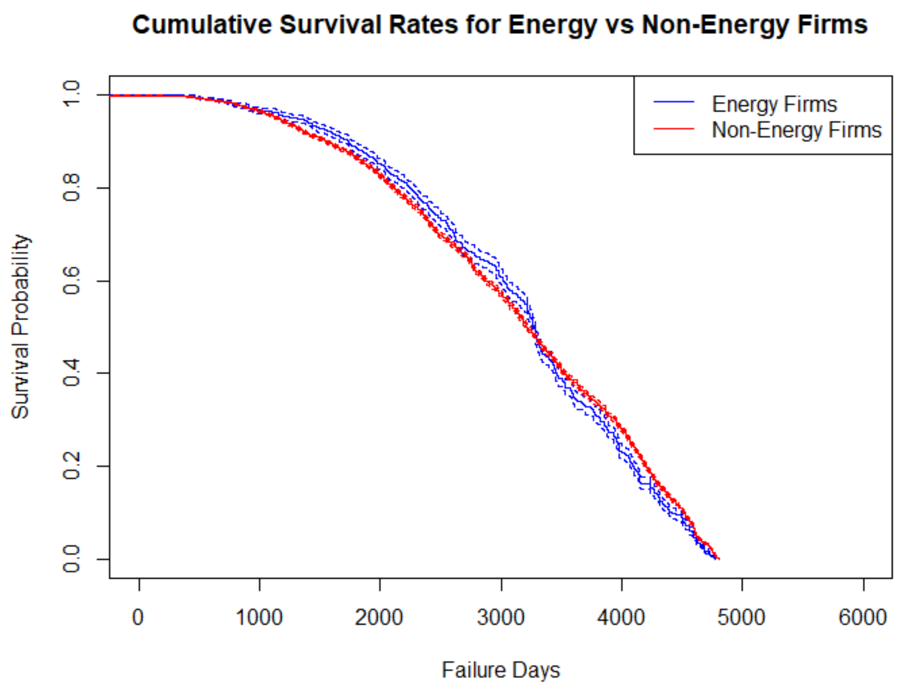


Figure A.8: **Cumulative survival rates for energy versus non-energy firms.**This graph compares the cumulative survival probabilities of energy firms (in blue) and non-energy firms (in red) over the observation period from 2010 to 2022. The x-axis represents the time duration in days, while the y-axis shows the cumulative survival probability. The curves indicate the proportion of firms surviving up to a specific time point, highlighting the differences in survival rates between the two groups.

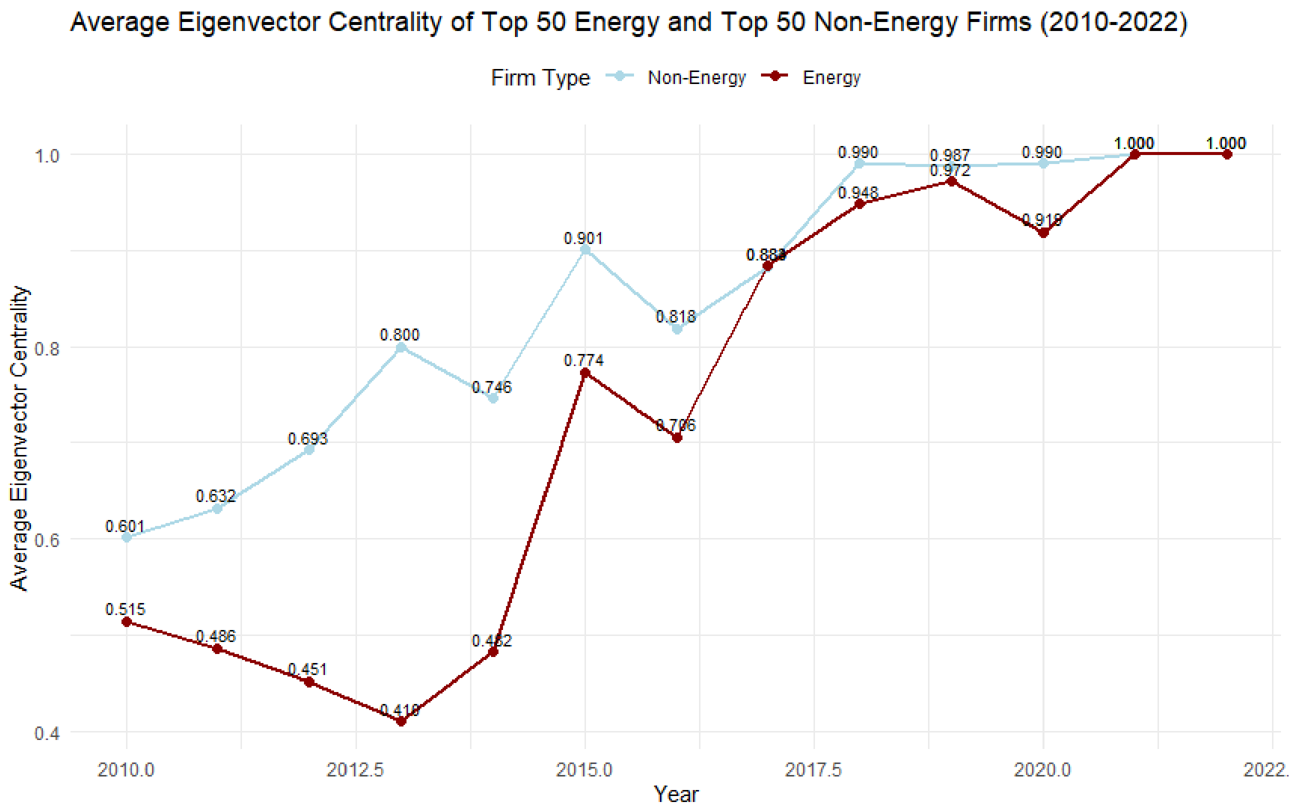


Figure A.9: **Time Series of Average Eigenvector Centrality for Top 50 Energy and Top 50 Non-Energy Firms (2010–2022).** This figure presents the average eigenvector centrality of the top 50 energy firms (in dark red) and top 50 non-energy firms (in light blue) from 2010 to 2022. The eigenvector centrality serves as an indicator of systemic importance within the network of corporate failure, where higher values suggest greater influence and potential for risk propagation.

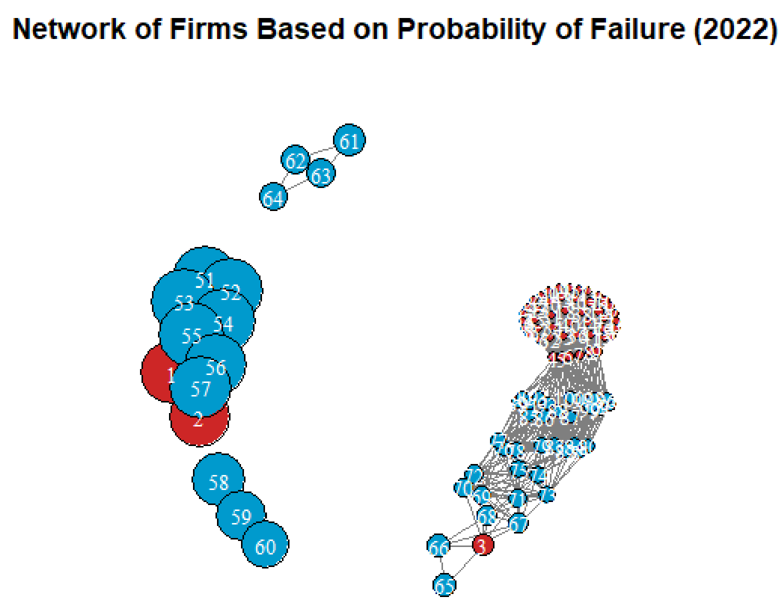


Figure A.10: **Network Visualization of Top 50 Energy and Top 50 Non-Energy Firms Based on Probability of Failure in 2022.** This network graph illustrates the interconnectedness of the top 50 energy (red nodes) and top 50 non-energy firms (blue nodes) by eigenvector centrality, representing systemic risk. Node size reflects the predicted probability of failure, with larger nodes indicating higher failure risk.

Chapter 2

From Climate to Economy: Understanding Climate Risks in the U.S. Market

Abstract

To what extent do asset markets effectively price climate risk focusing on the responsiveness of U.S. firms to climate change? Do state-level climate risks materially influence the market valuation of U.S. firms? The primary aim of our research is to delve into the extent to which asset markets accurately price climate risk, with a particular focus on climate transition and physical risk. Specifically, our aim is to investigate whether U.S. firms' proactive responses to climate-related challenges are adequately reflected in market valuations. A key contribution of our study is incorporating a state-level climate change indicator into the model. It is imperative to acknowledge that not all U.S. states are equally equipped to respond to the policy void in the U.S. This necessitates a nuanced approach to risk measurement. The challenge lies not in disentangling state risk from nationwide risk, but rather in recognising the significance of state-level information. By incorporating state-level risks into our analysis, we aim to highlight their importance in optimising portfolios. Neglecting state-level risks renders portfolios suboptimal, as it represents a critical risk factor that cannot be overlooked. Our results show that U.S. climate policy uncertainty and economic conditions significantly explain portfolio returns. State-level factors such as temperature anomalies, economic policy uncertainty, and economic conditions offer deeper insights into risk and performance, with temperature anomalies notably affecting returns.

2.1 Introduction

The Earth's changing climate poses profound and escalating challenges, with particularly important implications for the U.S. economy given the uncertainty surrounding its macroeconomic and financial consequences. Financial regulators increasingly view climate change as a material source of corporate risk and emphasize the need to assess and manage the spillovers from climate-related shocks across firms and sectors. In this context, understanding how climate-driven transition risks propagate through U.S. financial markets is essential for informing effective regulation and guiding resilient economic and investment strategies.

Our primary objective is to investigate whether asset markets appropriately price climate risk, particularly climate transition and physical risk, and, notably, whether U.S. energy sector, manufacturing, and transportation proactive responses to it are factored into these market valuations. Additionally, we aim to understand how different states in the U.S. implement climate change policies and measure climate-specific transition risks at the state level. To address these crucial inquiries, we pose a pivotal research question: "To what extent do asset markets effectively price climate risk, particularly transition risk, focusing on the responsiveness of U.S. firms to climate challenges? Furthermore, how does the implementation of climate policies across diverse U.S. states influence national-level transition risks, and are these risks adequately factored into market valuations of U.S. firms?". More specifically, we seek to understand how firms in different U.S. states are affected by climate risks and uncertainties.

Our research methodology is underpinned by a core principle of invariance, crucial for addressing the challenge of omitted variables in asset pricing. By accounting for arbitrarily rotated factors that comprehensively cover the factor space, we ensure a consistent estimation of risk premia, even in scenarios where underlying risk exposures remain unidentified. Inspired by the work of Giglio and Xiu (2021) we advocate the application of Principal Component Analysis (PCA) to reconstruct the factor space. Subsequently, we employ Principal Components (PCs) as controls in cross-sectional regressions alongside observable factors. Our approach is designed to accommodate the inherent differences in data frequencies. Often, factors of interest, such as climate risk indicators, are available only at lower frequencies compared to returns, which are typically accessible at higher frequencies. Recognizing this challenge, we emphasize the importance of adopting the mixed-frequency adaptation of the methodology proposed by Giglio and Xiu (2021). This adaptation is crucial to effectively capture and analyse the dynamics of climate risk factors across different temporal scales.

Given the complexity of climate risk, it is challenging to capture a company's exposure across all dimensions with a single measure. This study focuses on two key aspects: climate transition risk and physical risk. To enhance the analysis, we integrate a state-level climate change indicators, examining how U.S. firms respond to climate challenges amidst the varied capacities of states to address gaps in federal policy.

Our findings demonstrate that market valuations effectively incorporate responses to climate and economic risk factors, as evidenced by statistically significant coefficients and risk premia across various models. The inclusion of multiple principal components enhanced model fit and refined the estimation of risk premia, underscoring the robustness and validity of our results. Key factors such as climate policy uncertainty (CPU_{US}), economic policy uncertainty (EPU_{US}), and economic conditions ($ECON_{US}$) exhibited diverse impacts on portfolio performance, reaffirming their significance in financial modelling and empirical asset pricing. Additionally, the analysis of the Partisan Conflicts Index (PCI_{US}) offers a novel perspective on the influence of political polarization and policymaking dysfunction on asset pricing, complementing earlier findings on economic policy uncertainty at both national (EPU_{US}) and state levels (EPU_{States}). While all three risk factors capture dimensions of political and economic uncertainty, their impacts on portfolio returns vary in scope and magnitude, highlighting nuanced differences.

This analysis not only aligns with established financial principles but also offers valuable insights into the pricing of state-level risk factors, such as temperature anomalies ($Tanomalies$), emphasizing the significant implications for climate-sensitive sectors. Furthermore, robustness checks reveal that smaller firms exhibit higher risk premia across most factors, including climate risk factors, suggesting that these firms are more vulnerable to climate-related risks and demand a higher premium to compensate for such exposures. These findings underscore the importance of incorporating comprehensive climate risk assessments into investment strategies, particularly for portfolios with substantial exposure to smaller firms.

Not all U.S. states are equally equipped to address the policy void left by federal inaction on climate change. Research highlights that partisanship (Bromley-Trujillo et al., 2016; Egan and Mullin, 2017; Benegal and Scruggs, 2018), economic considerations (Huang et al., 2007; Chandler, 2009; Matisoff and Edwards, 2014), exposure to climate impacts, and issue salience (Bromley-Trujillo and Poe, 2018; Bromley-Trujillo, Holman, and Sandoval, 2019) significantly influence a state's willingness to enact climate policies. However, partisan divides and the lobbying power of fossil fuel and utility sectors often impede progress, leaving many states hesitant to implement robust climate measures. Despite these challenges, sub-national initiatives, such as state-level greenhouse gas reduction targets and participation in programs like the Regional Greenhouse Gas Initiative (RGGI), demonstrate states' potential to substantially contribute to national and global climate goals (Fosten and Nandi (2023)).

This research shifts the focus from national policies to a more nuanced analysis of regional climate risk, emphasizing the importance of state-level dynamics. Sub-national actions are increasingly recognized as critical to achieving emissions reductions, as reflected in the growing prominence of local initiatives on global platforms. For instance, the "Cities, Regions, and Built Environment" day at COP26[1] highlighted the role of cities and regions in combating climate change. Approximately half of U.S. states have established emissions targets, with over ten actively participating in initiatives like the RGGI, a market-based program aimed at emissions reduction (Fosten and Nandi (2023)). This divergence between federal and state policies, particularly along partisan lines, underscores the need for research that captures the localized nature of climate risks.

A central objective of this study is to assess state-level climate risk, with a specific focus on climate transition risk. Given the impracticality of capturing daily or weekly fluctuations in climate news and policy changes, we adopt a monthly data approach. This methodology, supported by a mixed-frequency adaptation of Giglio and Xiu (2021), enables a comprehensive analysis of climate risk factors at both national and state levels, providing critical insights into the interplay between sub-national initiatives and broader market dynamics.

Monthly data has proven critical for capturing the multifaceted dimensions of physical and transition climate risks in recent research. For instance, Sheng, Gupta, and Çepni (2022) analysed the impact of temperature growth and volatility on climate risk across 50 U.S. states using data from 1984 to 2019. Similarly, Yang, Caporin, and Jiménez-Martin (2022) examined climate transition risk spillovers in six major financial markets, utilizing month-end CO2 emissions as a proxy due to data limitations. Furthermore, Campos-Martins and Hendry (2023) investigated the global effects of climate change news on financial markets, integrating daily and monthly climate indices provided by Ardia et al. (2023) and R. F. Engle et al. (2020) to offer a comprehensive view. The challenges of timely environmental data availability are well-documented. For example, Fosten and Nandi (2023) highlighted the lack of up-to-date information on regional CO2 emissions and energy consumption in U.S. states, constrained by annual data publication schedules and significant lags. This underscores the difficulty of real-time monitoring, a critical consideration for climate risk analysis.

[1]The UN Climate Change Conference of the Parties (COP26) at the Scottish Event Campus (SEC) in Glasgow on 31 October – 13 November 2021, brought parties together to accelerate action towards the goals of the Paris Agreement and the UN Framework Convention on Climate Change.

In light of data limitations, we adopt a mixed-frequency framework following Giglio and Xiu (2021), combining monthly climate indicators (e.g., CO_2 emissions, temperature anomalies, Climate Policy Uncertainty (CPU), and Economic Policy Uncertainty (EPU)) with daily firm-level returns. Using a three-pass estimation procedure, we estimate risk premia for observable climate factors while mitigating the impact of omitted or unobservable factors. This approach is well suited to the scarcity of high-frequency, state-level climate data and allows us to robustly assess how climate risks are priced at both the national and state levels.

Conventional estimators of risk premia in linear asset pricing models may be biased when certain factors are omitted, as highlighted by Giglio and Xiu (2021). To address this issue, they propose a three-pass method to estimate the risk premium of an observable factor, even when not all factors are specified or observed. This methodology aligns with our research objectives, where we encounter a mix of observed and unobserved risk factors, particularly climate transition risk at both the state and national levels. According to Giglio and Xiu (2021), the risk premium of an observable factor can be accurately identified as long as the combined set of observed and unobserved factors spans the true factor space.

Investors are increasingly concerned with non-tradable risks, such as climate-related factors, which are not readily captured by traditional portfolios (Giglio, Kelly, and Stroebel (2021)). Estimating the risk premium of these non-tradable factors requires constructing a tradable portfolio that isolates these risks while holding other factors constant. However, conventional risk premium estimators, like the Fama-MacBeth (1973) approach, are vulnerable to omitted variable bias when models fail to account for all priced sources of risk. Our research, like Giglio and Xiu (2021), seeks to address this limitation by applying their novel three-pass methodology, which leverages the high dimensionality of available assets and the concept of rotation invariance to recover the risk premium of observable factors, even when not all true risk factors are included in the model. We contrast the results from this methodology with those obtained from the traditional Fama-MacBeth (1973) model.

The three-pass methodology by Giglio and Xiu (2021) is grounded in the principles of rotation invariance, applicable to risk premia within linear factor models. They consider a model with p factors and aim to estimate the risk premium associated with one factor (g_t). The key insight is that the risk premium of g_t remains unaffected by rotating the $p-1$ control factors. This implies that linear combinations of the original factors can serve as controls, as long as the rotated model captures the same underlying risk. Giglio and Xiu (2021) show that knowing the identities of all true factors is not necessary for estimating the risk premium of a specific factor. Their approach combines principal component analysis (PCA) with two-pass cross-sectional regressions to provide consistent estimates of the risk premium for any observed factor. This methodology is well-suited for our research, where unobserved climate-related factors and their associated risk premiums are central to understanding market dynamics.

Drawing on insights from Campos-Martins and Hendry (2023), future research on geo-climatic volatility could incorporate individual- or country-level climate news, as variations in climate exposures may reflect differences in policy stringency, activism, geological events, and carbon emissions. Recent evidence also shows that both physical and transition climate risks are reflected in financial markets: a market-based physical risk factor validated around large natural disasters and a stranded-asset transition factor jointly explain time-varying climate exposures and stress-sensitive capital shortfalls in the insurance sector Jung et al. (2024). Building on these insights, our research aims to fill a gap in the literature by being the first to jointly analyse climate transition and physical risks across U.S. energy and energy-dependent firms, explicitly leveraging cross-state variation in climate policy at both state and federal levels and examining how this heterogeneity shapes firms' climate risk profiles.

Measuring firm-level climate risk exposure presents several challenges. Despite growing regulatory pressure and investor demand for transparency, firms remain reluctant to disclose their climate risk exposure. This is particularly evident in the limited availability of carbon emissions data, often restricted to traditional sectors like manufacturing and utilities, and the omission of indirect carbon costs embedded in supply chains (Shapiro (2021)). Moreover, the evolving nature of climate change creates uncertainty about its long-term effects on firms, complicating both government and corporate decision-making (Barnett, Brock, and Hansen (2020)). Additionally, while historical emissions data is useful for assessing past practices, forward-looking perspectives are increasingly vital for understanding a firm's climate exposure and its adaptability in the transition to sustainability, key to advancing climate finance research (Giglio, Kelly, and Stroebel (2021)).

To address these challenges, our research aims to bridge the gap in climate risk literature by enhancing the measurement of transition risk, often referred to as "carbon risk," within the U.S. market. We focus on understanding the intersection of climate risk, political uncertainty, and economic factors, analysing a comprehensive dataset of U.S. energy firms and firms highly dependent on energy. By addressing these complexities, we seek to contribute valuable insights into firm-level climate risk exposure, helping improve risk management strategies and support informed decision-making in the transition to a sustainable economy.

Investors and financial regulators are increasingly recognizing the risks associated with climate change, sparking a growing body of research on the complex relationship between climate transition risks and physical climate risks. While this area of study remains less developed compared to more traditional finance topics, there is a noticeable shift toward understanding how climate-related events impact various markets and sectors. Climate risks are generally categorized into two primary types: (1) physical risks, which refer to the direct impacts of climate events, both acute (e.g., droughts, floods, wildfires) or chronic (e.g., rising temperatures, loss of biodiversity), and (2) transition risks, which arise from inadequate responses to climate change and the need for businesses to adapt to sustainable practices, such as low-carbon manufacturing. These distinctions are explored in the work of scholars like Giglio, Kelly, and Stroebel (2021), FSB (2022), Stroebel and Wurgler (2021), Meinerding, Schüler, and Zhang (2024)[2], Baudino and Svoronos (2021) and Kruttli, Tran, and Watugala (2025). As financial markets face the growing pressures of climate change, understanding these distinct risk categories is crucial for investors and regulators alike. As Giglio, Kelly, and Stroebel (2021) points out, recognizing and differentiating between these risk types is essential, as they often do not materialize simultaneously and can have varying impacts on asset valuations.

In this research, we focus primarily on transition risk, while also incorporating selected metrics of physical risk, which has traditionally been the focus of much existing literature. According to Campos-Martins and Hendry (2023), news of specific natural disasters is unlikely to significantly impact global financial markets unless such events become more frequent. As a result, investors often discount physical risks due to their long-term nature, whereas transition risks tend to manifest in the short term. Despite the close relationship between physical and transition risks, literature suggests that physical risks are more localized and predictive, and their long-term effects may be overlooked by investors. However, we include physical risks in our analysis by using the temperature anomalies indicator for each U.S. state and the climate policy uncertainty (CPU) index developed by Gavriilidis (2021). The CPU index, derived from news

[2]Meinerding, Schüler, and Zhang (2024) proposes an identification strategy for economy-wide transition risk shocks grounded in a stranded-assets framework, where transition shocks can be interpreted as sudden increases in the long-run default probabilities of carbon-intensive firms. The approach exploits two observable implications: green firms should outperform brown firms and the repricing should coincide with major public climate-related news. Empirically, the identified shocks are often linked to political decisions rather than simple proxies such as carbon price movements, and they are shown to have sizeable aggregate and financial-stability effects while disproportionately affecting transition-sensitive sectors such as fossil fuels and energy.

coverage in eight major U.S. newspapers, serves as a proxy for both transition and physical risks at the national level.

Building on the work of Sheng, Gupta, and Çepni (2022), who examined the impact of climate risks, specifically temperature growth and volatility, on economic activity across 50 U.S. states from 1984 to 2019, we further integrate temperature anomalies ($Tanomalies$) as a physical risk indicator at the state level. Their study found a consistent negative impact of climate risks on economic activity, contingent on state-level economic and policy-related uncertainties. We compute $Tanomalies$ using temperature data from the National Oceanic and Atmospheric Administration (NOAA), enhancing our ability to examine the relationship between climate dynamics and economic activity at both the state and national levels. This approach allows us to explore both physical and economic risks in greater detail, offering a comprehensive view of climate-related challenges.

Hartlieb and Eierle (2024) examined whether auditors consider climate change-related risks when determining audit pricing. They found that clients with higher exposure to climate risks, as indicated by country-level proxies like natural disasters and societal awareness, incur higher audit fees. This supports our research aim of linking climate risk to firm financial performance. Specifically, by using physical climate risk measures at the county level, including the number of natural disasters and local climate change awareness, they found a positive correlation between audit fees and climate-related risks in the clients' headquarters counties.

To strengthen our analysis, we incorporate physical climate risk measures at the state level, using data from the Federal Emergency Management Agency (FEMA) (2024), on the number of natural disasters. This measure captures the impact of extreme weather events, which can significantly affect firm performance, as evidenced by previous studies (e.g., Chava, 2014; Huang et al., 2018). Given that climate change is increasing the frequency of various events, such as hurricanes, storms, and freezing temperatures, this approach provides a comprehensive view of the risks businesses face across U.S. states. Our use of state-level data also eliminates potential biases related to legal differences across counties, ensuring that our findings are more applicable to the U.S. context.

This measure improves upon prior research by including a wider range of natural disasters, such as heatwaves, droughts, floods, and severe cold, which are all exacerbated by climate change (e.g., Banholzer et al., 2014). By accounting for a broader spectrum of events, our approach offers a more holistic understanding of the physical climate risks that businesses encounter, enhancing the robustness of our analysis.

The findings of Campos-Martins and Hendry (2023) suggest that while acute physical climate risks may not trigger global shocks, chronic risks have no significant direct impact.

Transition risks, however, are intricately linked to policies, regulations, technological advancements, and evolving climate patterns, highlighting the need to account for both physical and transition climate risks in our analysis. As Yang, Caporin, and Jiménez-Martin (2022) points out, transition risk differs fundamentally from physical risk, and investors' expectations regarding climate policies, technological advancements, and physical risk collectively influence firms' exposure to transition risks, often leading to a reassessment of asset values.

The interconnection between physical and transition risks is apparent, as even regions not directly impacted by physical risks can face indirect consequences due to international relations with more vulnerable areas. Despite this overlap, the primary systemic risks to financial markets are anticipated to stem from exposure to transition risks, particularly in the case of a disorderly transition (Campos-Martins and Hendry (2023)). Recent literature has expanded to include various interconnected risks, such as regulatory and policy risks, technological shifts affecting sustainable energy competitiveness (Chenet et al. (2015), Gonzalez-Salazar, Kirsten, and Prchlik (2018)), and changes in social norms and legal frameworks. However, there is a significant gap in research, particularly in the energy market, which is highly influenced by government policies and subject to political and economic fluctuations. Our study aims to address this gap.

While several studies have examined the impact of climate change on real estate assets using physical climate risk factors (e.g., sea-level rise, flooding, and hurricanes), equity asset analysis lacks a comprehensive set of risk measures. Existing proxies, such as ESG ratings and CO2 emissions, are often criticized for their coverage and reliability (Stanny (2018)). As noted by Giglio, Kelly, and Stroebel (2021), there is significant room for improvement in climate risk exposure measures, particularly for equity assets. Moreover, measuring transition risk is challenging due to its unobservable nature, with researchers typically relying on proxies that capture only certain aspects of transition risk. This lack of precision in defining and measuring transition risk, as highlighted by Meinerding, Schüler, and Zhang (2023), poses a significant hurdle in understanding its full impact on firms and financial markets.

Recent studies, such as Giglio, Kelly, and Stroebel (2021), predict significant shifts in the pricing of climate risks over time, with investor focus on these risks emerging more recently. Global events, like the 2009 UN Climate Change Conference and the SEC's climate change disclosure guidance in 2010, have been key in shaping societal views on climate change (R. F. Engle et al. (2020)). Our research spans from March 1, 2000, to March 1, 2023, to capture these evolving dynamics in the pricing of climate risks.

This study contributes to the climate asset-pricing literature by identifying state-level climate risk as a distinct and economically relevant source of priced variation in returns, rather than treating climate risk as solely a national or aggregate phenomenon[3]. Existing work has shown that climate events can affect asset prices through expected cash flows, discount rates, and relative return premia between green and brown assets, with mixed evidence on whether a carbon risk premium is systematically priced (Bressan et al. 2023; Pástor, Stambaugh, and Taylor 2022). Building on this literature, we extend the analysis along two dimensions. First, we jointly examine transition and physical climate risks, rather than focusing on only one channel. Second, and more importantly, we show that these risks must be measured not only at the national level but also at the state level, where policy autonomy, exposure heterogeneity, and local economic structure can generate variation in climate-related shocks that aggregate measures obscure (Fosten and Nandi 2023).

Methodologically, the chapter contributes by constructing a climate-mimicking portfolio framework that maps innovations in climate news into ESG-sorted portfolios while incorporating both national and subnational climate information. In contrast to existing hedging approaches that primarily rely on aggregate climate news or broad measures of extreme events, our approach is designed to recover the asset-pricing content of localized climate risk, allowing us to test whether state-specific climate exposures contain information beyond national factors. This approach relates to the mimicking-portfolio methods developed by R. F. Engle et al. (2020) and Alekseev et al. (2022), while extending them to account for the pricing relevance of subnational climate exposures. This provides a more granular account of how climate risk enters portfolio returns and strengthens the empirical link between climate shocks and asset pricing.

The chapter's central insight is therefore not simply that climate risk matters, but that ignoring state-level climate risk leads to an incomplete characterization of the climate factor itself. In the U.S., where states retain substantial autonomy over climate policy, emissions targets, and implementation, transition risk is partly decentralized and cannot be fully inferred from national indicators alone (Fosten and Nandi 2023). The same logic applies to physical risk, whose incidence and economic consequences are inherently uneven across locations. By showing that portfolio design and hedging performance

[3] The identification of state-level climate risk as a priced factor relies on the assumption that the estimated climate factor is not merely a proxy for correlated regional or macroeconomic shocks. In particular, the empirical design assumes that, conditional on standard asset-pricing controls and observable regional and macroeconomic determinants, the remaining variation linked to climate exposure reflects a distinct source of systematic risk that is priced by investors. Under this interpretation, any residual co-movement in returns associated with climate exposure is attributed to climate-related risk rather than to omitted common shocks.

improve when state-level climate information is incorporated, the chapter argues that climate risk is priced partly through local channels. This shifts the contribution from a broad application of existing climate-finance tools to a more precise claim: subnational climate risk is not peripheral noise, but a missing dimension in climate asset pricing and portfolio optimization.

The structure of the paper is as follows: Section 2 details the methodology, Section 3 presents the key variables, data sources, and descriptive statistics, Section 4 discusses the empirical results, Section 5 provides robustness checks, and Section 6 concludes the study.

2.2 Literature Background:

In recent years, investor concerns regarding the spillover effects of climate change have grown significantly, as it affects asset returns through two primary channels: physical risk and transition risk (Clapp et al. (2017)). Physical risk encompasses financial losses or increased costs due to acute or chronic climate events, such as hurricanes, wildfires, and floods. Transition risk, often referred to as "carbon risk," arises from the economic adjustments necessary for transitioning to a low-carbon economy, driven by changes in policies, technological advancements, and shifting public preferences. This risk is especially tied to uncertainties around the pace and timing of the transition, which can lead to abrupt changes in asset prices, particularly in response to sudden policy shifts or carbon pricing legislation (Carney (2015)).

Expanding on this, Bolton and Kacperczyk (2023) introduced the concept of "carbon-transition risk," which encompasses a wide range of shocks, including shifts in climate policies, reputational impacts, market preferences, and technological innovations. While much of the literature focuses on how transition risk directly impacts the economy, less attention has been given to how these risks propagate across sectors and regions. Understanding the transmission of climate transition risk, particularly through inter-sectoral or interstate linkages, is crucial for grasping the interconnectedness of economic systems and the potential spillover effects across the broader economy.

Industries reliant on fossil fuels and energy-intensive operations are particularly vulnerable to transition risks. The pace of decarbonization plays a key role in determining long-term impacts, including asset fluctuations and the risk of "stranded" assets, as highlighted by the European Central Bank (ECB, 2019) and the Network for Greening the Financial System (NGFS, 2020). Additionally, legal risks associated with non-compliance with climate-related regulations and inadequate climate impact disclosures further amplify these challenges, underscoring the urgency for a comprehensive approach to managing climate-related financial risks.

Recognizing the critical role of U.S. state-level climate policies, Bergquist and Christopher Warshaw (2023) emphasized the need for a comprehensive measure of state-level climate policy. They developed an aggregate index spanning 2000-2020, based on 25 individual policies, revealing significant variations in state policies. Interestingly, their findings suggest that more stringent state climate policies do not harm state economies, highlighting the proactive role U.S. states play in mitigating climate change. This underscores the importance of understanding state-specific climate risks, a key focus of our research.

[Figure B.1 around here]

Figure B.1 underscores substantial cross-state heterogeneity in the U.S. clean-energy transition. While early adopters such as New York, California, and Massachusetts are broadly consistent with more liberal policy environments, other cases complicate this mapping: Texas and Ohio exhibited early leadership but subsequently retrenched, and states such as Colorado, Minnesota, and Washington implemented meaningful climate policies despite not being conventionally classified as "liberal." Taken together, these patterns suggest that climate-policy ambition is not a simple proxy for broader policy liberalism and should be measured as a distinct, state-specific dimension.

This distinction became especially salient during the Trump administration, which initiated wide-ranging rollbacks of federal climate and environmental regulations, amid rising investor attention to climate risk. Over this period, the U.S. withdrew from the Paris Agreement, replaced the Clean Power Plan, and relaxed standards affecting fuel economy and energy efficiency, alongside administrative changes at the EPA that weakened regulatory capacity and constrained state-level initiatives. Consistent with Rabe (2011), these federal shifts heightened the importance of state policy as an independent locus of climate governance, motivating our focus on state-level variation as a key source of differential climate risk exposure.

Importantly, states have not converged in their policy responses. Adoption has been slower where political opposition is stronger, where economic activity is more dependent on fossil fuels, and where lobbying and public support shape the feasibility of stringent regulation. This uneven policy landscape matters for our analysis because it directly affects how climate risks are priced and mitigated across firms and regions, and it informs the credibility and effectiveness of pathways toward national climate objectives and broader economic resilience.

Our research aligns with recent studies exploring firm-level measures of climate risk. For instance, Sautner et al. (2023) and Q. Li et al. (2020) use textual analysis of earnings call transcripts to quantify corporate climate risk, with a focus on the share of discussions related to climate topics. Sautner et al. (2023) introduce the Climate Change Exposure measure, finding that companies in countries with stronger climate regulations exhibit higher exposure. Unlike traditional carbon risk measures, much of the variation in climate exposure occurs at the firm level. Similarly, J. Kölbel et al. (2020) examine climate risk disclosures in annual reports and find that transition risks significantly impact CDS market spreads, while physical risks do not. Additionally, Huynh and Xia (2023) investigate the relationship between corporate bond returns and the Climate Change News Index, showing that bonds with high climate news betas are more expensive, potentially serving as hedges against climate risks. Kruttli, Tran, and Watugala (2021) empirically examine firm-level uncertainty arising from extreme weather events, particularly hurricanes, within a theoretical framework that distinguishes between "incidence uncertainty" (the likelihood of a firm being affected) and "impact uncertainty" (the severity of consequences if affected). Their findings indicate that stock options of firms located in hurricane landfall regions experience significant increases in implied volatility both before and after impact, suggesting that investors initially underestimate uncertainty. However, this under-reaction diminishes following Hurricane Sandy, indicating a learning effect. Despite hurricanes being idiosyncratic shocks, the study demonstrates that they influence firms' expected returns through both cash flow and discount rate channels. Additionally, the persistence of hurricane-related discussions in earnings calls long after landfall highlights the prolonged nature of uncertainty. These findings align with the argument in this research that firms remain insufficiently adapted to extreme weather risks and that markets struggle to efficiently price novel climatic risks, underscoring inefficiencies in how extreme weather-related uncertainty is incorporated into asset prices especially at U.S. state level.

Our research aligns with studies exploring the impact of climate-related risks on portfolio performance. For example, Alekseev et al. (2022) examine climate hedging portfolios constructed by mutual fund managers after local extreme heat events. Van der Ploeg and Rezai (2020) focus on the vulnerability of fossil fuel assets to market devaluation, highlighting the role of transition risk driven by renewable technology advancements and evolving climate policies such as the Paris Agreement. They suggest that assets in these industries face heightened exposure to market uncertainties, with the return on a stranded asset portfolio serving as a proxy for market expectations regarding the transition to a low-carbon economy. This proxy reflects investor sentiment on the risks associated with sustainability shifts in global markets.

Additionally, Fang, Hsu, and Tsou (2023) investigate the existence of a "pollution premium" in U.S. stock returns, focusing on mandatory toxic emissions disclosures rather than greenhouse gases. Their study reveals a 5.52% annual return spread on a long-short portfolio based on toxic emissions, attributing this "pollution premium" to the higher regulatory risks faced by polluting firms. This further emphasizes the broader impact of climate-related risks on financial market dynamics.

Our research builds on recent studies examining the stock return implications of corporate carbon emissions, with significant contributions from Bolton and Kacperczyk (2021), who explore U.S. and global equity markets. They find that higher emissions are associated with elevated returns, with indirect emissions showing explanatory power beyond industry effects. Their work also uses levels and percentage changes in emissions as proxies for long-term and short-term transition risks, identifying a transition risk premium primarily in North American, European, and Asian stocks. In addition, early contributions such as Hong, G. Andrew Karolyi, and Scheinkman (2012) emphasize that climate change introduces a systematic source of uncertainty with implications for financial markets and investor behaviour. More recent work provides stronger evidence on the asset-pricing relevance of climate risk. For example, R. Bansal, Kiku, and Ochoa (2021) show that climate change risk is priced in financial markets, highlighting how long-run climate uncertainty affects expected returns and valuation. At the firm level, N. M. Pankratz, Rob Bauer, and Zehner (2023) demonstrate that climate change exposure affects firm performance and generates investor surprises, supporting the view that physical climate risk has economically significant valuation effects. Together, these studies reinforce the idea that climate risk is not only a macro-financial concern but also a source of cross-sectional variation in returns and firm outcomes.

Our study extends the emerging literature on transition risk, which, while still in its early stages, is rapidly expanding. Bolton and Kacperczyk (2023) observed that companies with higher carbon emissions often experience heightened stock returns across various sectors and regions, including Asia, Europe, and North America. This aligns with the theoretical predictions of Pástor, Stambaugh, and Taylor (2022), who suggested lower expected returns for green assets, and with empirical evidence from Giglio, Kelly, and Stroebel (2021), which shows retail investors anticipating negative returns on ESG investments.

Additionally, we build on the work of R. F. Engle et al. (2020) and Alekseev et al. (2022), who found that stocks with lower climate risk exposure tend to outperform during periods of negative climate-related news. This nuanced view highlights the dynamic relationship between climate risk exposure and stock performance, offering valuable insights into how market sentiment and climate-related news interact. Our research further contributes by examining spillover risks and liquidity dynamics, enhancing the understanding of these complex financial market relationships.

In a parallel vein, Faccini, Matin, and Skiadopoulos (2023) made a noteworthy contribution by constructing news-based risk factors intricately linked to both physical and transition risks. Their findings shed light on the fact that climate policy risks, notably, are now embedded in U.S. stocks, particularly gaining prominence after 2012. Adding depth to our comprehension, Choi, Z. Gao, and Jiang (2020) documented the underperformance of carbon-intensive firms relative to those with lower carbon emissions during periods of unusually high local temperatures. This underscores the heightened sensitivity of investors to climate risks under specific environmental conditions.

Turning our attention to climate physical risks, Acharya, Johnson, et al. (2022) revealed a compelling association between higher heat stress exposure among S&P500 corporations and a 45 basis points higher (un-levered) expected return per annum. This trend has been consistently observed since 2013. Additionally, Cuculiza et al. (2021) emphasised that sell-side equity analysts actively incorporate climate news into their earnings forecasts, illuminating the market's sensitivity to climate change events as reflected in analysts' forecast revisions.

The current research on measuring systemic climate risk primarily relies on static, retrospective approaches, often using deterministic transition scenarios. This contrasts with more advanced studies on the systemic risk of financial institutions, particularly during financial crises, with key contributions from R. Engle (2004), Allen et al. (2012), Adrian and Brunner-Meier (2016), and Acharya and Thakor (2016). Similarly, Bua et al. (2022) examine physical and transition climate risk premia in euro area equity markets, developing novel indicators based on text analysis to assess climate risk premiums.

Q. Li et al. (2020) contribute to firm-level climate risk measurement by analysing earnings call transcripts, distinguishing between physical and transition risks. Their study finds that firms exposed to high transition risk, particularly those that do not proactively address it, have been undervalued, reflecting growing investor concern over climate issues. They also highlight that proactive responses, such as reducing carbon intensity, are linked to more effective efforts to mitigate climate risks.

Building on these approaches, our research combines measures of both physical and transition climate risks to address a critical gap in climate finance literature: the pricing of climate risk in capital markets. By incorporating both risk dimensions, we offer a more comprehensive perspective on how climate risks influence asset valuations, contributing to the ongoing development of this field.

In the realm of assessing climate risk, various methodologies have been employed to measure the global financial landscape and its inherent vulnerabilities. For instance, studies such as that by R. Engle (2004) adopt an approach focused on common volatility shocks, capturing contemporaneous movements that simultaneously impact all financial markets. Alternatively, other measures leverage innovative techniques like text mining, as exemplified by Ardia et al. (2023), who construct a daily Media Climate Change Concerns index using news articles from major U.S. newspapers and newswires. In alignment with these approaches, we incorporate a similar climate risk factor based on U.S. newspaper coverage proposed by Gavriilidis (2021), allowing for analysis across a broader time span. This risk factor facilitates a comprehensive examination of climate-related concerns and their potential implications for financial markets.

According to Rebonato et al. (2023), asset prices often exhibit limited responsiveness to climate-related news, presenting a challenge in aligning market reactions with the anticipated economic effects of climate policies. While climate risk introduces additional volatility to asset prices, Rebonato et al. (2023) argues that market prices often underestimate or overlook the impact of both transitional and physical climate risks on companies' cash flows. Unlike more observable factors such as unemployment or inflation, climate risk lacks a clear, tangible proxy, making its integration into market valuations more complex. This muted price sensitivity to climate news creates a puzzle, as it contradicts the expected economic outcomes of climate policies. Our research seeks to address this gap by improving the measurement of climate risk, focusing on both physical and transitional risks, and thereby enhancing our understanding of their effects on asset pricing.

Macroeconomic models, such as integrated assessment models (e.g., Nordhaus (2018) and Golosov et al. (2014)), often use carbon pricing to internalize climate externalities and explore the social cost of carbon in equilibrium. While these models offer valuable insights, practical applications like those by the Network for Greening the Financial System (NGFS) turn to scenario analysis to navigate transition risks. However, historical evidence shows that the implementation of climate policies is complex, influenced by factors like policy timing, suboptimal policy mixes, uncertainty, international coordination, technology advancements, and shifting consumer preferences.

The existing literature on systemic climate risk predominantly relies on static, retrospective measures linked to deterministic transition scenarios. This contrasts with the more dynamic approaches used in assessing systemic risk within financial institutions, particularly during financial crises, as seen in the works of R. F. Engle et al. (2020), Adrian and Brunner-Meier (2016), and Acharya and Thakor (2016). For instance,

R. Engle (2004) examines common volatility shocks that affect all financial markets simultaneously, while Ardia et al. (2023) employs text mining techniques to track climate change concerns in U.S. media, using a daily Media Climate Change Concerns index.

Additionally, Campos-Martins and Hendry (2023) propose a novel approach for assessing common movements in the Oil and Gas industry, leveraging a global volatility framework. Meanwhile, Son et al. (2023) uses vector autoregressive models (VAR) to analyse liquidity spillovers between ETFs and their underlying portfolios, offering another methodological perspective for studying systemic climate risks. Our research contributes to this evolving landscape by exploring new methods to measure and understand climate transition risk.

Overall, this comprehensive body of research serves as a robust foundation for our own inquiry, spotlighting the intricate ways in which climate risks are interwoven with U.S. market. It underscores the multi-dimensional relationship between climate-related factors and stock prices. As we navigate the literature gap concerning climate transition risk effects on the energy and highly depended energy markets, it is crucial to acknowledge the dynamic interplay between these risks and the ever-evolving market landscape.

2.3 Methodology:

Aligned with the framework proposed by Giglio and Xiu (2021), our methodology unfolds in three distinct phases. Initially, we employ Principal Component Analysis (PCA) to extract factors and their loadings from a comprehensive panel of test asset returns, thereby reconstructing the factor space, which represents an unknown rotation of the p factors. Subsequently, we conduct a cross-sectional regression solely utilizing the Principal Components (PCs), excluding the factor of interest, g_t, to ascertain their respective risk premia. In the third step, we proceed to estimate a time series regression of g_t onto the PCs, illuminating the relationship between g_t and the latent factors while mitigating potential measurement errors associated with g_t. The risk premium of g_t is subsequently derived as the product of its loadings on the PCs (computed in the third step) and their respective risk premia (computed in the second step). According to the authors, the invariance principle elucidated above ensures the robust identification of the risk premium associated with g_t, irrespective of the rotation of true factors occurring during the extraction of PCs.

In this section, we introduce the three-pass risk premia estimator devised by Giglio and Xiu (2021), which effectively addresses both omitted variable and measurement error biases encountered in the estimation of risk premia within linear factor models. Let us consider a general linear factor model comprising p factors:

$$r_t = \beta\gamma + \beta v_t + u_t, \quad \text{where} \quad E(v_t) = E(u_t) = 0, \quad \text{and} \quad \mathrm{Cov}(u_t, v_t) = 0 \tag{2.1}$$

The authors Giglio and Xiu (2021) define v_t as the innovations of the p factors, this means the zero factors, r_t represents the excess returns on each n portfolios of assets, u_t represents the idiosyncratic error terms, β are factor loadings, and γ represents the vector of risk premia for the p factors.

Thus, this methodology empowers us to analyse the factor loadings of the risk premia associated with climate-related risk factors (g_t), even in the absence of complete observation of all true factors (v_t).

Let g_t be a set of d observable factors whose risk premia we will estimate. The term g_t is related to the unobservable factors v_t as follows:

$$g_t = \delta + \eta v_t + z_t, \quad \text{where} \quad E(z_t) = 0, \quad \text{and} \quad \mathrm{Cov}(z_t, v_t) = 0 \quad (2) \tag{2.2}$$

Where η represents the relation between g_t and the unobservable factors v_t, and z_t is a measurement error in g_t. The risk premium of g_t is defined as the expected excess return of a portfolio with a beta equal to 1 with respect to g_t and a beta equal to 0 with respect to all other factors[4] (including the unobservable variables), and this corresponds to: $\gamma_g = \eta\gamma$.

From the preceding equations (1) and (2), it becomes evident that neither η (the loading of g_t on the unobservable factors) can be identified if the factors v_t remain unobserved. Addressing this challenge, as outlined by Giglio and Xiu (2021), hinges on a potent property inherent to risk premia in linear factor models, termed rotation invariance. This property states that the product $\eta\gamma$ can be identified even if one observes only an arbitrary full-rank rotation of the factors. This means, if one just observes $\hat{v}_t = Hv_t$, where H is a full-rank $p \times p$ matrix but observes neither v_t nor H. Having that in consideration, we can rewrite the model as following:

$$r_t = \beta H^{-1} H\gamma + \beta H^{-1} H v_t + u_t, \tag{2.3}$$

$$g_t = \delta + \eta H^{-1} H v_t + z_t. \tag{2.4}$$

Assuming that $\hat{\eta} = \eta H^{-1}$, $\hat{\gamma} = H\gamma$, and $\hat{\beta} = \beta H^{-1}$, we can rewrite the model in terms of the rotated factors $\widehat{v}_t$:

$$r_t = \hat{\beta}\hat{\gamma} + \hat{\beta}\widehat{v}_t + u_t, \tag{2.5}$$

$$g_t = \delta + \hat{\eta}\widehat{v}_t + z_t. \tag{2.6}$$

Assuming that $\widehat{v}_t$ needs to be observed in order to identify $\hat{\eta} = \eta H^{-1}$ (represents the vector of regression coefficients of g_t on $\widehat{v}_t$) as well as $\hat{\gamma} = H\gamma$ (represents the risk premia of $\widehat{v}_t$, which can be obtained via standard cross-sectional regressions). According to Giglio and Xiu (2021), we cannot recover η or γ separately because we do not know H, we can still identify the risk premium of g_t due to: $\hat{\eta}\hat{\gamma} = \eta H^{-1} H\gamma = \eta\gamma = \gamma_g$.

It is important to note that this invariance property is just a specific property to γ_g and it does not hold for other quantities in the model, such as η, γ, or β.

Following these steps, the Giglio and Xiu (2021) three-pass procedure first estimates the rotated factors $\widehat{v}_t$ via PCA. Second, it estimates, via a two-pass cross-sectional regression, $\hat{\gamma} = H\gamma$, meaning it estimates the risk premia of $\widehat{v}_t$. Third, it estimates $\hat{\eta} = \eta H^{-1}$ by using a time series regression of g_t onto the estimated $\widehat{v}_t$. Additionally, the risk premia of g_t, $\eta\gamma$, can be ultimately estimated by taking the product of the estimates of $\hat{\eta}$ and $\hat{\gamma}$ from the previous steps.

Following these steps, the Giglio and Xiu (2021) three-pass procedure first estimates

[4] According with Giglio and Xiu (2021) this specification nests the case where g_t is the first factor by choosing η to be the vector $(1, 0, 0, 0, \ldots, 0)$ and setting δ and z_t to zero.

the rotated factors $\widehat{v}_t$ via PCA. Second, it estimates, via a two-pass cross-sectional regression, $\hat{\gamma} = H\gamma$, meaning it estimates the risk premia of $\widehat{v}_t$. Third, it estimates $\hat{\eta} = \eta H^{-1}$ by using a time series regression of g_t onto the estimated $\widehat{v}_t$. Additionally, the risk premia of g_t, $\eta\gamma$, can be ultimately estimated by taking the product of the estimates of $\hat{\eta}$ and $\hat{\gamma}$ from the previous steps.

Having presented a broader idea surrounding the Giglio and Xiu (2021) methodology, the next subsection delves deeper into the three-pass estimator. This subsection discusses in detail the role of each step. After that, subsection 2 discusses the methodology's application to mixed-frequency data.

2.3.1 The Three-Pass Estimator

First, the model assumes constant risk premia and loadings. According with Giglio and Xiu (2021) is recommended to use in this methodology a characteristic-sorted portfolios instead of individual stocks. Following the main asset pricing literature, one of the main advantages of using portfolios is that their risk exposure is more stable over time.

Second, the model assumes weak restrictions on the structure of the errors, and remains applicable in the presence of nonstationarity, heteroskedasticity, and dependence in both the time-series and cross-sectional dimensions.[5]

Third, the model imposes that the zero-beta rate is equal to the observed treasury bill rate.

In this model, we denote, similar to Giglio and Xiu (2021), R as the $n \times T$ matrix of excess returns, V the $p \times T$ matrix of factors, G the $d \times T$ matrix of observable factors, U the $n \times T$ matrix of idiosyncratic errors, and lastly, Z the $d \times T$ matrix of measurement error. According to Giglio and Xiu (2021), the model can be written as the following:

$$R = \beta\gamma_T^\top + \beta V + U. \tag{2.7}$$

Writing $(\bar{R}, \bar{V}, \bar{G}, \bar{U}, \bar{Z})$ as the respective matrices of the demeaned variables, the previous

[5]This robustness is nevertheless conditional on the maintained factor structure underlying the estimator. In particular, cross-sectional dependence is assumed to be captured by a finite number of common latent factors, while the remaining idiosyncratic component is only weakly dependent across assets. Hence, the consistency and inference properties of the estimator rely on the assumption that pervasive co-movement in returns is well approximated by this factor representation. If cross-sectional dependence is stronger than assumed, or arises from forms not adequately captured by the latent factor structure, the estimated coefficients may remain less reliable and standard errors may be distorted, potentially overstating statistical significance.

equation can be written as the following:

$$\bar{R} = \beta \bar{V} + \bar{U}. \tag{2.8}$$

We need only the demeaned version of equation (2), given that for non-tradable factors, the mean of g_t, δ, does not have a meaningful relevance or interpretation. We can write in matrix notation g_t as the following:

$$\bar{G} = \eta \bar{V} + \bar{Z}. \tag{2.9}$$

This methodology does not require the true factors V to be known or observed; it only makes use of the excess returns R and the factors of interest G.

According to Giglio and Xiu (2021), this model guarantees that by applying PCA to the panel of observed return innovations $\bar{R}$, we can recover both β and $\bar{V}$ up to some invertible matrix H as long as $n, T \to \infty$.

According to the three-pass estimator, and given observable returns R and the factors of interest G, the three-pass steps of the estimator for $\gamma_g = \eta\gamma$ can be written as follows:

PCA step: According to this step, we should extract the principal components (PCs) of returns by conducting the PCA of the matrix $\frac{1}{nT}\bar{R}^T\bar{R}$. Define the estimator for the respective factors and their loadings as:

$$\hat{V} = T^{\frac{1}{2}} \left(\xi_1 : \xi_2 : \ldots : \xi_{\hat{p}}\right)^T \quad \text{and} \quad \hat{\beta} = T^{-1}\bar{R}\hat{V}^T, \tag{2.10}$$

where $\xi_1, \xi_2, \ldots, \xi_{\hat{p}}$ represents the normalized eigenvalues (of length 1) corresponding to the largest $\hat{p}$ eigenvalues of the matrix $\frac{1}{nT}\bar{R}^T\bar{R}$ and $\hat{p}$ is some consistent estimator of the number of factors that follows specific assumptions (Giglio and Xiu (2021)). Thus, this step recovers the factors v (by rotating $H\bar{V}$ for some unobserved invertible matrix H) by extracting the PCs of returns and selecting the first $\hat{p}$ of them. Giglio and Xiu (2021) propose to extract the PCs from the $T \times T$ matrix, $\frac{1}{nT}\bar{R}^T\bar{R}$, and normalize the estimated factors such that $\hat{V}\hat{V}^T = I_p$. Once the PCs are extracted in this stage, the second stage estimates their risk premia.

Cross-sectional regression step: In this step, we run a cross-sectional ordinary least squares (OLS) regression of average returns ($\bar{R}$) onto the estimated factor loadings ($\hat{B}$), with the objective of obtaining the risk premia of the estimated latent factors:

$$\hat{\gamma} = \left(\hat{\beta}^T\hat{\beta}\right)^{-1}\hat{\beta}^T\bar{r}. \tag{2.11}$$

The estimation of the risk premia in this step can be done in several ways. Similar to Giglio and Xiu (2021), we decided to estimate using an OLS regression for simplicity[6].

Time series regression step: The last step is characterized by running a time series regression of g_t onto the extracted factors from the first step and then obtaining the estimator $\hat{\eta}$, and the fitted value of the observable factor, $\hat{G}$, as follows:

$$\hat{\eta} = \hat{G}\hat{V}^T \left(\hat{V}\hat{V}^T\right)^{-1}, \tag{2.12}$$

$$\hat{G} = \hat{\eta}\hat{V}. \tag{2.13}$$

As stated before, the estimator of the risk premium for the observable factor g_t is obtained by combining the estimate results from step 2 and step 3:

$$\hat{\gamma}_g = \hat{G}\hat{V}^T \left(\hat{V}\hat{V}^T\right)^{-1} \left(\hat{\beta}^T\hat{\beta}\right)^{-1} \hat{\beta}^T\bar{r}. \tag{2.14}$$

The three-pass estimator can be written as:

$$\hat{\gamma}_g = \hat{G}\hat{V}^T \left(\hat{V}\hat{V}^T\right)^{-1} \left(\hat{\beta}^T\hat{\beta}\right)^{-1} \hat{\beta}^T\bar{r}. \tag{2.15}$$

In sum, this final step stands as a notable contribution of Giglio and Xiu (2021) to the literature, augmenting the standard two-pass procedure with a critical third step. As highlighted by Giglio and Xiu (2021), this step holds particular significance as it bridges the gap between the opaque risk premia associated with latent factors and those predicted by economic theory. This aspect is crucial for addressing our research question, as it allows for the consideration of latent factors as climate risk variables at both national wide and state level. Given the limited availability of high-frequency climate risk factors and economic policy indicators at both U.S. wide and state level, with accurate information only accessible at a monthly frequency, we have chosen to employ the three-pass estimation methodology for mixed frequencies outlined by Giglio and Xiu (2021). This approach is particularly suited for scenarios where g_t, representing factors such as macroeconomic and climate data, is available solely at a lower frequency (e.g., monthly), while returns of test assets are accessible at a higher frequency (e.g., daily); see Appendix B for further details.

[6]According with Giglio and Xiu (2021) it is possible to estimate the risk premia using either generalized least squares (GLS) regression or weighted least squares (WLS) regression, but either of the two estimations will require estimating a larger number of parameters. Thus, these estimators will not improve the asymptotic efficiency of the OLS to the first order.

2.4 Data

We conducted our empirical analysis on a dataset comprising 20 portfolios, collectively representing 1287 U.S. firms[7] across 38 different U.S. states[8]. Having a large cross-section and an extended time series of test assets is essential for ensuring the consistency and desirable asymptotic properties of the three-pass estimator. Additionally, a substantial number of test assets is recommended by Lewellen et al. (2010), who express scepticism regarding asset pricing tests based on a limited cross-section of assets with potentially strong low-dimensional factor structures. A robust dataset helps mitigate concerns about model misspecification and enhances the reliability of our empirical findings.

In this research, similar to R. F. Engle et al. (2020), we accumulate the monthly asset returns of firms into portfolios based on firm characteristics. Specifically, we use the ESG combined scores of firms to model their risk exposures. We implement this characteristics-based approach by utilizing firm-level environmental performance scores constructed by the ESG data provider Thomson Reuters [9]. These scores are employed as characteristics to sort individual stocks and form portfolios.

The risk exposures of individual assets depend directly on these characteristics, so sorting the assets by characteristics ensures that the resultant portfolios have constant risk exposures. In the context of our analysis, firms are ranked from 1 to N (where N is the total number of firms, in this case, 1287) based on their ESG scores. Rank 1 is assigned to the firm with the highest ESG combined score, while rank N is assigned to the firm with the lowest ESG score. To facilitate a more nuanced analysis, the rankings are standardized to a range between -0.5 and +0.5 (standardized rank =

[7]This research includes data on both energy sectors and firms that are highly dependent on energy, such as those in manufacturing, utilities, and transportation, thereby encompassing information on both energy providers and users.

[8]In this research, the scope of analysis was confined to 38 U.S. states, a limitation dictated by the availability of data relevant to our study. The dataset includes only those states where the firms under investigation are located, thus defining the geographical boundaries of our analysis. The states represented in this research include: Alabama, Arizona, Arkansas, California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Indiana, Kansas, Maryland, Massachusetts, Michigan, Minnesota, Missouri, Nebraska, Nevada, New Hampshire, New Jersey, New Mexico, New York, North Carolina, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Vermont, Virginia, Washington, and Wisconsin.

[9]The ESG Combined Score is an overall firm score, between 0 to 100, based on the reported information in the environmental, social and governance pillars (ESG score) with an ESG controversies overlay. It provides an overall assessment of a company's performance in these areas, indicating its commitment to sustainability, responsible business practises, and ethical conduct. The higher the score the better is the firm performance. Note that ESG combined scores (annual) are not available for every time period between 2000 and 2023. To address this data gap, we use forward fill and/or backward fill methods, applying the most recent available ESG score for each firm in instances where the score is missing for a particular year. Additionally, the same corresponding ESG combined score is attributed to all months within the same year.

$(rank - 0.5)/N$). This standardization allows for a consistent comparison across firms. Consequently, portfolio 1 includes firms with the lowest ESG scores according to the Eikon Database, whereas portfolio 20 comprises firms with the highest ESG scores. Each portfolio thus reflects a spectrum of ESG performance based on standardized rankings. This portfolio-based approach offers a more granular understanding of regional climate risks and facilitates the analysis of how these risks impact asset pricing and portfolio performance. This approach offers several advantages. Firstly, it allows for the creation of a robust and extensive panel of test assets, facilitating the estimation of principal components [10] in the initial step without additional assumptions. Moreover, portfolios provide test assets with more stable exposures (i.e., betas) to risk factors, as portfolio weights reflect time-varying risk exposures captured by firm characteristics.

Our approach in this paper builds on measures of firms' environmental exposures produced by third-party ESG data providers. There has been a growing interest in ESG investing among investors, who are increasingly demanding assets that fulfil certain environmental (E), social (S), and governance (G) criteria. Given this trend, measuring the ESG characteristics of firms has become an important task for investors. Firm-level ESG scores are available from numerous providers that collect raw data from sources such as firms' disclosures, SEC filings, and reports by governments or NGOs. These raw data are then translated into numerical ESG scores using proprietary algorithms.

Our approach aligns with the methodology outlined by Giglio and Xiu (2021), which emphasizes the analysis of portfolio returns in relation to various factors. In our analysis, we incorporated both state-specific and nationwide climate risk factors. Notably, the methodology proposed by Giglio and Xiu (2021) is well-suited for large datasets, allowing for the inclusion of multiple test portfolios without significant computational costs. This framework provided a robust foundation for our research, enabling us to comprehensively evaluate climate risk disparities among U.S. states and their implications for asset pricing.

Moreover, our dataset covers a substantial period from March 1, 2000, to March 1, 2023, encompassing a total of $T = 277$ months, with an average of approximately 21.74 trading days per month. Daily adjusted close prices were sourced from the

[10] Our research utilizes the approach established by Giglio and Xiu (2021) to estimate the dimension of the factor space, denoted as $\hat{p}$, which indicates the number of latent factors. This approach considers both the number of latent factors and a maximum allowable factor count ($p_{\max}$). Instead of relying solely on information criteria, their method is supported by the empirical behaviour of eigenvalues, ensuring analytical consistency. Applying this approach, we observed a significant drop in eigenvalues beyond the 10th principal component of the covariance matrix of returns. Thus, we set $p_{\max}$ to 10, as the first ten components capture most of the significant variance in the dataset, reflecting the underlying factor structure suggested by the data. This parameter setting enhances our factor model, aligning with established empirical finance practices and better representing the complexities of financial returns data.

Eikon database for all included firms, enabling us to compute accumulated returns. Since we apply a mixed-frequency methodology following Giglio and Xiu (2021), we accumulated the excess returns to align firm information with a monthly frequency. This adjustment allows us to harmonize high-frequency data with monthly risk factors, ensuring consistency in our analysis. We then aggregated this data into distinct portfolios based on the firms' specific ESG characteristics.

The inclusion of a large cross-section of potentially diverse test assets, as in our study, adheres to recommendations by Lewellen et al. (2010). They caution against asset pricing tests relying on small cross-sections with a strong, low-dimensional factor structure. By contrast, our approach leverages a broad range of portfolios, enhancing the robustness and generalizability of our findings across different market conditions and risk environments. By combining firm-level excess returns with state-specific risk factors, we aim to uncover the nuanced effects of climate transition and physical risks across different U.S. states. This methodology allows us to bridge the gap between high-frequency financial data and lower-frequency risk indicators, providing a robust framework for our empirical analysis. This approach not only enhances the precision of our findings but also underscores the importance of incorporating regional environmental factors into financial modelling and decision-making.

[Table B.1 around here]

Table B.1 presents summary statistics for the monthly returns of the 20 portfolios. Mean monthly returns range from -0.00551 (portfolio 4) to 0.00624 (portfolio 20), indicating variability in portfolio performance, with some portfolios showing positive returns while others underperformed. Median returns corroborate these findings, showing consistent performance trends across the period. Portfolios with lower mean returns, such as Portfolio 1, 2, and 4, suggest higher exposure to negative risk factors, whereas Portfolios 19 and 20 exhibit higher returns, potentially due to superior ESG practices or favourable market conditions. Standard deviation ranges from 0.00149 (portfolio 20) to 0.00914 (portfolio 1), reflecting varying levels of return volatility. Higher standard deviations in portfolios 1 and 3 indicate greater risk and volatility, while lower values in Portfolios 16 and 20 suggest more stable performance. Skewness values range from -3.00706 (Portfolio 1) to 1.63249 (portfolio 13), with negative skewness prevalent across most portfolios, indicating a tendency for returns to be lower than the mean, with potential for extreme negative returns. kurtosis values range from 1.88071 (portfolio 15) to 12.16327 (portfolio 7), indicating distributions with heavier tails than a normal distribution. Portfolios 1, 6, and 7 exhibit high kurtosis, suggesting a higher likelihood of extreme returns. These findings underscore significant risk exposure across portfolios and highlight the importance of understanding the risk-return trade-off in ESG-oriented investments.

Overall, the variation in mean returns across portfolios emphasizes that firms with higher ESG scores may offer distinct risk and return profiles, reinforcing the need for thorough due diligence when integrating ESG factors into investment strategies.

While the asset pricing literature has proposed an extremely large number of factors (Harvey et al. (2016), McLean and Pontiff (2016)), in this research we focus on a few representative ones that we consider important for our main research objective. Additionally, following Giglio and Xiu (2021) the risk premia estimate[11] for any factors using the three-pass methodology do not depend on whether other factors are included in g_t.

The factors under consideration encompass both tradable and non-tradable categories. Tradable factors include market returns (in excess of the risk-free rate), size (SMB), and value (HML) provided by Fama-French three factor models[12] (Wharton Research Data Services (2024)). Additionally, we incorporate the Fama-French five equity factors -market (MKT), size (SMB), value (HML), operating profitability (RMW), and investment (CMA) - as defined by Fama and French (2015). These factors are obtained at a monthly frequency providing a comprehensive set of variables to analyse asset returns and their sensitivities to various market dynamics. Non-tradable factors comprise indicators of economic activity at both national and state levels, as well as climate risk metrics encompassing both transitional and physical risks.

To gauge economic activity, we utilize economic indexes at both the state ($ECON_{States}$) and national levels ($ECON_{US}$), sourced from Baumeister, Leiva-Leon, and Sims (2021). This data allows us to capture the economic development of each state and its broader impact on portfolio performance. The economic condition indicators enable us to study the responses of individual states to a range of macroeconomic shocks, natural disasters like droughts, hurricanes, and wildfires, and federal economic policies. These policies include fiscal, monetary, trade, and industrial measures, as well as state-specific fiscal measures, environmental regulations, transportation policies, infrastructure programs, energy market (de)regulation, property tax reforms, and land-use rules.

[11]Recall that the observable factors g_t in the three-pass methodology proposed by Giglio and Xiu (2021) can be either an individual factor or groups of factors. In our research g_t represents a group of factors.

[12]The Fama-French portfolios are constructed from the intersections of two portfolios based on size, measured by market equity (ME), and three portfolios based on the ratio of book equity to market equity (BE/ME), which serves as a proxy for value. The returns from these portfolios are used to construct the Fama-French factors. Eugene Fama and Kenneth French demonstrated that these factors capture a statistically significant portion of the variation in stock returns.

As additional measures of policy uncertainty, we incorporate economic policy uncertainty indicators at both the state (EPU_{States}) and U.S. - wide levels (EPU_{US}), obtained from PolicyUncertainty.com (n.d.), with data available on a monthly basis. As per the methodology provided by the authors, a higher index value indicates heightened levels of uncertainty. The construction of the EPU index entails an exhaustive process, involving the analysis of daily and weekly newspapers from Washington DC and each state across the United States, including national papers like the NY Times or Wall Street Journal. EPU_{States} is tailored to assess uncertainty stemming from state and local policy matters. Each state-specific policy term set encompasses descriptors for executive positions, legislative bodies, policy initiatives subject to citizen votes, and regulatory bodies overseeing diverse sectors such as environment, labour, transportation, banking, energy, utilities, and financial services. This tailored approach ensures that the set of terms is unique to each state, reflecting the distinct titles, officials, regulatory bodies, and departmental structures across states. By leveraging the EPU_{States} indicator, our research offers a nuanced analysis of how state-level policies and regional economic dynamics influence climate change risk across states, while also assessing whether these policies are reflected in firm returns. This granular perspective enhances our understanding of the unique challenges and opportunities associated with climate change adaptation and mitigation efforts at the U.S. state level.

The increasing polarization in American politics over recent decades has led to significant government dysfunction, prompting the need to consider its economic implications. To capture this, we incorporated a novel high-frequency indicator of partisan conflict (PCI_{US}[13]) in the U.S., developed by Azzimonti (2018), as an additional risk factor in our analysis. According to Azzimonti (2018) and existing economic theories, heightened economic policy uncertainty or greater volatility in fiscal shocks tends to suppress economic activity. However, it is important to note that EPU can also arise from factors unrelated to partisan conflict, such as uncertainty over monetary policy or policy decisions by foreign governments. By incorporating the partisan conflict index as a risk factor, we aim to better understand its role in driving economic uncertainty and

[13]The partisan conflict index is a high-frequency measure constructed using a search-based methodology. It quantifies the frequency of newspaper articles that report disagreements among lawmakers about policy, both within and between national political parties, normalized by the total number of articles published within a given period. This approach provides a comprehensive indicator of partisan conflict over an extended time-frame. Philadelphia (2018) demonstrates that the long-term trend of this index mirrors patterns in political polarization and income inequality, underscoring its relevance to economic analysis. Philadelphia's findings suggest a strong correlation between economic policy uncertainty (EPU) and partisan conflict, both measures often moving in tandem. For example, legislative deadlines, such as those for fiscal policies, force policymakers to make critical decisions by specific dates, thereby amplifying uncertainty about future economic policy.

its broader impact on U.S. firms.

Prior studies have employed various methods to measure climate risks, including country-level climate risk indices, the occurrence of specific extreme weather events in particular regions (Dessaint and Matray (2017)), corporate climate-related disclosures, and firm-level carbon emissions. In this research we incorporated the Climate Policy Uncertainty Index for the U.S. (CPU_{US}), developed by Gavriilidis (2021). This index serves as a proxy for the national-level climate risk index[14]. Gavriilidis (2021) establishes the link between the CPU index and CO2 emissions. By analysing the scaled frequency of articles across eight major U.S. newspapers, the CPU index captures significant events pertaining to climate policy. Gavriilidis (2021) find a robust and negative relationship between climate policy uncertainty, as measured by the CPU index, and CO2 emissions, both at the aggregate and sectoral levels. This suggests that higher levels of uncertainty regarding climate policy tend to discourage energy consumption and non-essential transportation while incentivise renewable energy adoption and climate-friendly innovations, ultimately leading to reduced CO2 emissions. Consequently, we view the CPU index as a critical climate risk indicator for our analysis, providing valuable insights into the dynamics between climate policy uncertainty and emissions outcomes, not only measuring climate physical risk but as well climate transition risk.

[**Figure B.2 around here**]

Figure B.2 plots the U.S. Climate Policy Uncertainty index (CPU_{US}) from 2000 to 2023 and shows a distinctly event-driven pattern. The series is characterised by sharp, short-lived spikes that align closely with major announcements, regulatory initiatives, and legal or political turning points in climate governance. Early fluctuations coincide with pivotal moments such as the U.S. debate over international commitments (e.g., the Kyoto Protocol) and successive UN climate negotiations. In later years, spikes become

[14] Gavriilidis (2021) employs a comprehensive search strategy to identify relevant articles in eight prominent U.S. newspapers. These articles contain specific terms related to climate policy and uncertainty, as well as keywords associated with environmental regulations and legislation. The selected terms include variations such as "uncertainty" or "uncertain" and "carbon dioxide" or "climate" or "climate risk" or "greenhouse gas emissions" or "greenhouse" or "CO2" or "emissions" or "global warming" or "climate change" or "green energy" or "renewable energy" or "environmental" and ("regulation" or "legislation" or "White House" or "Congress" or "EPA" or "law" or "policy" (including variants such as "uncertainties", "regulatory", "policies", etc). Gavriilidis' search covers the period from April 1987 onwards. The eight newspapers included in the study are the Boston Globe, Chicago Tribune, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today, and the Wall Street Journal. For each newspaper, the number of relevant articles per month is scaled relative to the total number of articles during the same month. Subsequently, these scaled series are standardized to have a unit standard deviation and then averaged across newspapers on a monthly basis. Finally, the averaged series are normalized to ensure a mean value of 100 for the period spanning from April 1987 to August 2022. This rigorous methodology allows for a comprehensive analysis of climate policy uncertainty trends across major U.S. newspapers over the specified time frame.

larger and more frequent, reflecting a more contested policy environment in which climate regulation is repeatedly revised, challenged in court, or reframed through high-profile federal actions and international commitments. Prominent surges appear around episodes such as the Volkswagen emissions scandal, the announcement of U.S. withdrawal from (and subsequent re-entry into) the Paris Agreement, and major regulatory and judicial milestones affecting emissions standards. The index reaches particularly elevated and volatile levels in the late-2010's and early-2020's, consistent with heightened uncertainty during periods of rapid policy change, litigation risk, and large-scale legislative packages (e.g., the Inflation Reduction Act).

These dynamics highlight that climate-policy risk is not smoothly evolving, but instead concentrated in discrete uncertainty shocks that can plausibly influence market expectations, discount rates, and sectoral cash-flow prospects. Importantly, the national index may mask substantial regional heterogeneity: states differ markedly in policy ambition, implementation capacity, and exposure to regulatory change, implying that the transmission of climate-policy uncertainty to firms and investors can vary across locations. Incorporating state-level variation therefore helps disentangle aggregate from regional climate-policy risk and provides a sharper lens on how heterogeneous policy environments shape market dynamics and portfolio outcomes.

To assess climate physical risk measures, we incorporate temperature anomalies ($Tanomalies$[15]) at the state level. In their study, Sheng, Gupta, and Çepni (2022) examine the impact of climate risk, specifically temperature growth and its volatility, on the coincident indicator of the 50 U.S. states using a panel data setup spanning from 1984 to 2019. Their findings reveal that climate risks exert a negative influence on economic activity, irrespective of variations in temperature growth or its volatility. Importantly, they highlight that the detrimental effects of climate risks depend on the economic and policy-related uncertainty regime within states. Following a similar analytical approach, we include temperature anomalies ($Tanomalies$) as an additional indicator of climate physical risk at each U.S. state level, collected on a monthly basis.

Sheng, Gupta, and Çepni (2022) provide robust evidence supporting the hypothesis that higher levels of economic and policy-related uncertainty exacerbate the adverse effects of climate risk on economic activity. They suggest that elevated uncertainty amplifies the supply and demand-side transmission channels through which temperature growth and temperature anomalies and its volatility affect the real economy. Consequently, we consider temperature anomalies as a vital climate physical risk measure at

[15] We utilize average temperature data (in degrees Fahrenheit) for each state sourced from the National Centers for Environmental Information (NOAA/NCEI) (n.d.). State-level temperature anomalies are calculated as deviations from long-term historical monthly average temperatures.

the U.S. state level, essential for our comprehensive analysis.

Finally, as an additional measure of climate physical risk at the U.S. state level, we utilize the number of natural disasters declared by the Federal Emergency Management Agency (FEMA [16]) in each county.

Following Hartlieb and Eierle (2024), we use NOOA[17] declared-disaster data to construct a state-level physical climate risk index. Our monthly measure ($Natural_{Risk}$) counts the total number of disasters declared in the firm's headquarter state over the previous five years, while noting that this proxy may be imperfect because large firms' operational exposures can differ substantially from their headquarters location. This construction is motivated by evidence that extreme weather events (notably hurricanes) induce persistent firm-level uncertainty that is reflected in market prices and can carry return implications (Kruttli, Tran, and Watugala (2025)).

As an additional measure of climate transition risk factors at the state level, we incorporated the climate policy index developed by Bergquist and Christopher Warshaw (2023). This index, constructed using data from 25 individual policies, provides a comprehensive measure of state-level climate policies over the period 2000–2020. By capturing variations across states that are often overlooked in single-policy analyses, the climate policy index enables a more nuanced understanding of regional climate policy dynamics. Including this indicator in our analysis underscores the significance of state-level risk factors and their role in shaping the broader landscape of climate transition risks.

Finally, table B.2 provides details on the data code and scope utilized in this research.

[Table B.2 around here]

[16]FEMA dataset, known as Disaster Declarations Summaries, provides a summarized account of all federally declared disasters, beginning with the first disaster declaration in 1953. It includes all three types of disaster declarations: major disasters, emergencies, and fire management assistance. The dataset features declared recovery programs and geographic areas, with county-level data available from 1964 onwards.

[17]The NOOA dataset encompasses relatively large disasters that have had a significant impact on local economies. It includes information on the incident type (e.g., flood, storm, fire, hurricane, snow, tornado, earthquake), event start and end dates, affected areas (state and county), and types of assistance programs declared.

2.5 Empirical Results

In this section, we present our main empirical findings. We extract the set of latent factors from the panel of asset returns and relate them to a large set of tradable and non-tradable observable and unobserved factors. The traditional equity factors, such as the Fama-French factors, show different sensitivities to risk premia. While unobserved factors such as climate policy uncertainty in the U.S. (CPU_{US}) and the U.S. economic conditions indicator ($ECON_{US}$) exhibit significant explanatory power on portfolio returns. These findings elucidate how both observed and unobserved factors influence the performance of energy firms with specific ESG characteristics. Moreover, incorporating state-level risk factors, such as temperature anomalies ($Tanomalies$), economic policy uncertainty (EPU_{State}), and economic conditions ($ECON_{State}$), provides deeper insights into portfolio performance and risk. Our results indicate that these state-level factors are statistically significant and should be carefully integrated into portfolio management strategies for more robust risk assessment and mitigation. Specifically, certain state-level factors, such as temperature anomalies ($Tanomalies$), appear to be priced over the cross-section of returns and have substantial implications for portfolio performance. While the impact of economic policy uncertainty and economic conditions is relevant, it may not be as pronounced or consistent. Investors should therefore consider these state-level factors in their portfolio strategies, with particular emphasis on climate-related risks.

2.5.1 Latent Factor Structure of the Large Panel of Assets

We begin by analysing the latent factor structure of U.S. firms' returns, following the methodology of Giglio and Xiu (2021) to estimate the dimension of the factor space, denoted by $\hat{p}$. This dimension represents the number of latent factors identified in the data, with the maximum allowable number of factors, $p_{\max}$, determined from the empirical behaviour of the eigenvalues. Rather than relying exclusively on information criteria, this approach emphasizes the stability and economic relevance of the principal components recovered from the return covariance matrix.

Table B.3 reports the risk premia associated with U.S.-wide latent factors, measured as the ratio of each factor's eigenvalue to the sum of all eigenvalues of the sample covariance matrix constructed from the 20 test portfolios. The first column reports the intercept, corresponding to the zero-beta rate, while the remaining columns report the estimated risk premia for the extracted factors. Instead of conventional standard errors, Table B.3 presents variance estimates for the risk premia, providing a measure of estimation uncertainty for each specification. Each row corresponds to a different estimate based on $\hat{p}$, ranging from 1 to $p_{\max}$.

Our analysis reveals a marked decline in the eigenvalues of the covariance matrix after the 10th principal component, suggesting that the first ten components capture the economically relevant common variation in returns. We therefore set $p_{\max} = 10$, which is consistent with the underlying factor structure of the data and provides a parsimonious but sufficiently rich representation of return comovement.

[Table B.3 around here]

In Table B.3, the intercept, which represents the estimated zero-beta rate, is consistently close to 0.0045 across specifications. This stability is useful because it provides a benchmark level of expected return in the absence of factor exposure and suggests that the baseline pricing relation is not being driven by instability in the intercept term.

More importantly, the estimated risk premia vary substantially across factors, and these differences are economically informative. The contribution of this section is therefore not merely that some factors are statistically significant, but that several of them are sufficiently large in magnitude to matter for expected returns and portfolio allocation. In this context, the estimated premium should be interpreted as the compensation associated with one unit of exposure to the corresponding factor, holding other relevant channels constant within the model. The sign and size of the premium therefore provide information about whether investors view exposure to that source of risk as requiring compensation and about the relative importance of that risk in the cross-section of returns.

Among the traditional Fama-French factors, the size premium (SMB) and the value premium (HML) remain economically relevant, with positive premia of 0.1761 and 0.2774, respectively. These magnitudes suggest that the cross-section of returns in our sample continues to reflect established style-based dimensions of risk. By contrast, the market factor (MKT) exhibits a near-zero premium of -0.0099, indicating that once the broader factor structure is accounted for, the aggregate market factor contributes relatively little additional pricing power in this setting. Extending the analysis to the Fama-French five-factor framework, HML and CMA continue to display sizeable positive premia, while RMW has a negative premium of -0.1612. Taken together, these results suggest that the return differences across the ESG-sorted energy portfolios are not explained solely by aggregate market exposure, but by more specific dimensions of systematic risk.

Turning to the non-tradable factors, climate policy uncertainty in the U.S. (CPU_{US}) carries a positive premium of 0.1063. Economically, this indicates that firms or portfolios that are more exposed to fluctuations in climate policy uncertainty are associated with higher expected returns, consistent with investors requiring compensation for bearing transition-related policy risk. The magnitude of this premium is smaller than that of HML or EPU_{States}, which suggests that climate policy uncertainty is not the dominant driver of returns in the sample, but it is sufficiently large to be economically relevant. This finding reinforces the view that transition risk is reflected in asset prices, while also indicating that its pricing effect operates alongside, rather than instead of, broader macro-financial forces.

A particularly important result concerns state-level temperature anomalies ($Tanomalies$), which exhibit a positive premium of 0.1422. This estimate is economically meaningful because its magnitude is comparable to, and in some cases larger than, several conventional pricing factors included in the analysis. The result therefore goes beyond statistical significance: it implies that exposure to localized physical climate conditions is associated with a non-trivial return differential across portfolios. In economic terms, investors appear to require compensation for holding assets more exposed to state-level temperature fluctuations, consistent with the idea that localized climate disruptions affect firms' operating conditions, costs, and expected cash flows. This is central to the chapter's contribution, since it indicates that climate risk is not only an aggregate or national phenomenon but also operates through geographically differentiated channels that matter for asset prices.

At the same time, the interpretation of $Tanomalies$ should remain disciplined. Although temperature anomalies are clearly climate-related by construction, the premium attached to this factor may also reflect broader regional economic channels, such as local demand conditions, energy infrastructure vulnerabilities, production disruptions, or state-specific policy responses. For that reason, the result should be interpreted as evidence that a climate-related state-level variable is priced in the cross-section of returns, rather than as proof that the latent factor space isolates a purely climate channel with no macroeconomic overlap. This distinction is important because the three-pass estimator extracts common return variation, and such variation may simultaneously reflect climate, macroeconomic, and policy forces.

A similar pattern emerges for state-level economic policy uncertainty (EPU_{States}) and state-level economic conditions ($ECON_{States}$), which display positive premia of 0.2241 and 0.1700, respectively. These are among the largest premia in the table, and their economic significance is therefore substantial. In particular, the premium on EPU_{States} exceeds that of EPU_{US}, indicating that localized policy uncertainty appears more relevant for the pricing of these portfolios than broad national uncertainty. This is an economically important result because it suggests that firms' exposure to geographically concentrated policy and economic conditions is not diversified away in the cross-section of returns. Instead, investors appear to price these local risks directly, especially when they are likely to affect firms' operations, regulation, and financing conditions in uneven ways across states.

The comparison between national and state-level economic policy uncertainty further strengthens this interpretation. While both EPU_{US} and EPU_{States} are positively priced, the substantially larger premium for EPU_{States} suggests that state-level uncertainty has a more direct and economically consequential effect on the assets in our sample. Moreover, the variance estimate for EPU_{US} is considerably larger than that for EPU_{States}, implying that national policy uncertainty is priced with greater instability. By contrast, the smaller variance attached to EPU_{States} suggests that its pricing is not only stronger in magnitude but also more stable across specifications. This combination of larger point estimate and lower uncertainty makes the state-level result especially important from an economic perspective.

The results for the Partisan Conflict Index (PCI_{US}) add a further layer to the interpretation of political and policy risk. The estimated premium for PCI_{US} is negative, at -0.3114, and its absolute magnitude is one of the largest in the table. This result is economically significant because it suggests that exposure to heightened political polarization is associated with materially lower expected returns in the sample. One interpretation is that partisan conflict captures a form of aggregate political dysfunction that reduces confidence in future policymaking, depresses expected economic activity, or raises uncertainty in ways that are not compensated by a positive premium. This differs from the positive pricing of EPU_{US} and EPU_{States}, implying that not all forms of policy-related uncertainty operate through the same channel. While general policy uncertainty may raise required returns as compensation for risk, extreme political polarization may instead be associated with adverse expected cash-flow effects or persistent inefficiencies that lower valuations.

The comparison between PCI_{US}, EPU_{US}, and EPU_{States} therefore illustrates an important conceptual point for this chapter: state-level and national-level variables need not be interpreted as substitutes. Rather, they capture different layers of priced risk. State-level factors appear to proxy for localized exposures that are economically closer to firms' operating environments, whereas national political variables capture broader systemic conditions that influence discount rates, confidence, and aggregate expectations. This distinction helps clarify the interpretation of the latent factors as well. The latent factor structure should not be labelled climate-specific merely because climate-related variables load onto it. Instead, the latent space should be viewed as a common return component onto which climate, macroeconomic, and policy variables may project with different intensities.

The comparison between national and state-level economic conditions yields a similarly informative pattern. The premium on $ECON_{US}$ is negative (-0.0574), whereas the premium on $ECON_{States}$ is positive (0.1700). This contrast suggests that aggregate national economic conditions and localized state economic conditions affect returns through different mechanisms. National economic deterioration may depress expected returns by worsening aggregate demand or raising recession risk, while stronger state-level economic conditions may support firm-specific cash flows and create region-specific growth opportunities that investors reward. The larger magnitude and lower variance of $ECON_{States}$ again point to the stronger economic relevance of local conditions in the pricing of the portfolios considered here.

The variance estimates also provide useful evidence on the relative stability of the pricing results. The near-negligible variance of the zero-beta rate confirms the stability of the baseline return benchmark. By contrast, the variance of the risk premia differs substantially across factors, ranging from 0.1065 for EPU_{States} to 0.4404 for EPU_{US}. Importantly, the relatively low variance estimates for $Tanomalies$ (0.1188) and $ECON_{States}$ (0.1140) indicate that these factors are not only economically meaningful in magnitude but also comparatively stable in their pricing. This combination strengthens the interpretation that state-level factors are not incidental findings, but persistent components of the cross-sectional pricing relation in our sample.

Overall, the empirical results point to three main conclusions. First, economic significance matters: several of the estimated premia, especially those attached to $Tanomalies$, EPU_{States}, and $ECON_{States}$, are large enough to imply economically meaningful differences in expected returns across portfolios. Second, the findings support the view that state-level risk factors are particularly relevant for pricing, often more so than their national counterparts, which is consistent with the idea that geographically concentrated risks are important for firms with heterogeneous regional exposure. Third, the interpretation of the latent factor structure must remain cautious. The three-pass estimator successfully recovers priced common variation in returns and allows us to connect that variation to observable climate and macroeconomic variables, but it does not imply that the latent factors themselves can be given a purely climate-specific interpretation. The most defensible conclusion is therefore that climate-related state-level variables are economically and statistically relevant in the cross-section of returns, while operating alongside broader macroeconomic and policy channels that are also reflected in the latent factor space.

2.5.2 Risk Premia of U.S. Wide Factors

This subsection analyses a comprehensive set of tradable and non-tradable factors specific to the U.S. economy, including the climate policy uncertainty index (CPU_{US}), which serves as a proxy for both climate transition and physical risks. Additionally, we consider key macroeconomic factors such as the economic policy uncertainty index (EPU_{US}) and the economic conditions indicator ($ECON_{US}$), which captures the impact of climate risk shocks on the U.S. economy. We compare the risk premia associated with these U.S.-wide factors using both the Fama-MacBeth two-pass regression model and the methodology outlined by Giglio and Xiu (2021). Our analysis focuses on estimating the market price of risk (λ) for each factor. The dataset spans 277 months and includes 20 test portfolios, with a target factor for each model, assuming a maximum of $p_{\max} = 10$ principal components for the Giglio and Xiu (2021) methodology.

[Table B.4 around here]

Climate Policy Uncertainty Index

In Table B.4, the standard Fama-MacBeth (FM) estimates reveal an intercept of 0.0037, which is highly significant with a p-value less than 0.001, alongside a significant risk premium of 0.9555 ($p < 0.01$). This suggests a strong positive exposure to the CPU_{US} factor, indicating that climate policy uncertainty is priced into portfolio returns, reflecting its substantial role in the risk premium associated with the underlying portfolios.

In contrast, when applying the three-pass methodology (Table B.4) with 10 principal components (PCs), the intercept increases slightly to 0.0045, accompanied by a standard error of 0.0006. The estimated risk premium adjusts to 0.1063 with a standard error of 0.2000. The positive risk premium suggests that climate policy uncertainty is correlated with higher portfolio returns for U.S. firms with strong ESG characteristics. This indicates that investors demand a premium to bear the risk associated with climate policy uncertainty, signalling the growing importance of ESG factors in risk-return assessments.

The goodness-of-fit measure R_g^2 further supports these findings, showing that a significant portion of the variation in portfolio returns can be attributed to climate policy uncertainty. Specifically, for the CPU_{US} factor, the R_g^2 value of 0.5941 indicates that climate policy uncertainty plays a critical role in explaining the cross-sectional variation in returns, particularly for ESG-oriented portfolios. Overall, both models, standard Fama-MacBeth and Giglio and Xiu (2021), suggest that the CPU_{US} factor is indeed priced into U.S. portfolio returns, with the three-pass methodology providing a more nuanced adjustment in risk premia. The results highlight the critical importance of integrating climate-related factors, such as climate policy uncertainty, into investment strategies, given their substantial impact on asset returns, particularly for firms with high ESG scores. These findings align with prior research emphasizing the significant influence of climate policy uncertainty on economic and financial conditions Giglio, Kelly, and Stroebel (2021), FSB (2022), Stroebel and Wurgler (2021), and Baudino and Svoronos (2021). In addition, this study contributes to the growing literature on the intricate relationship between equity prices and climate change dynamics, which often presents contrasting findings.

Our results are also consistent with recent evidence from European equity markets showing that both transition and physical climate risks command economically meaningful risk premia, particularly in the post-2015 period. Specifically, Bua et al. (2024) document the emergence of sizeable annual premia of roughly 7.05% (transition) and 6.14% (physical) after 2015, with compensation increasing in the degree of exposure, reinforcing the interpretation that investors demand additional returns for bearing climate-related risks, consistent with our analysis. Importantly, their results also highlight that climate-risk pricing exhibits cross-country heterogeneity and that national and sub-national conditions matter for both investment decisions and climate policy design. This evidence complements our state-level findings and further motivates incorporating geographically granular climate risk measures when evaluating climate exposures and pricing implications.

For instance, Bolton and Kacperczyk (2021) and Bolton and Kacperczyk (2023) demonstrate that climate change is priced into financial markets, revealing that higher CO_2 - emitting firms tend to generate higher returns - while N. Bansal, Defo, and Lacasse (2021) show that low-frequency global temperature variations negatively affect global stock markets. Complementing these findings, Gong et al. (2023) report that increases in climate change risk tend to increase stock returns for fossil fuel companies in global markets. Additionally, Yang, Caporin, and Jiménez-Martin (2022) highlight that rising temperatures at the location of listed firms cause significant negative shocks to stock prices, with smaller and high book-to-market value firms being more adversely affected. Together, these findings underscore the multifaceted and region-specific nature of climate risk pricing in financial markets, reinforcing the need for a nuanced understanding of how climate policy uncertainty and broader climate dynamics shape equity returns. This study not only broadens the scope of existing literature but also emphasizes the importance of further exploring the interaction between climate-related risks and firm characteristics to develop more effective and sustainable investment strategies.

Macroeconomic Factors

In the standard Fama-MacBeth (FM) estimation, the intercept for EPU_{US} is estimated at 0.0035, with a standard error of 0.0001, indicating a highly significant baseline return across all portfolios ($p < 0.001$). The FM risk premia estimate of 1.6015 (Table B.4), accompanied by a standard error of 0.1395, signifies a strong positive relationship with economic policy uncertainty ($p < 0.01$). This suggests that firms react significantly to changes in regulatory or policy environments related to economic policy uncertainty, highlighting the impact of macroeconomic factors on portfolio returns.

When utilizing the three-pass methodology with 10 principal components (PCs), we observe consistent results in the analysis of EPU_{US}. The intercept remains stable at 0.0045, demonstrating robustness across different model specifications. However, the risk premia associated with EPU_{US} is lower at 0.0723 (Table B.4), with a relatively high standard error of 0.2917. This suggests some variability in the influence of economic policy uncertainty, indicating that the market's response to this factor may fluctuate depending on other conditions. These findings emphasize the need for more comprehensive factor models to capture the complex and sometimes uncertain effects of policy-related risks on financial markets.

Following the methodology outlined by Giglio and Xiu (2021), the inclusion of the Partisan Conflict (PCI_{US}) index as a risk factor in analysing U.S. firms' portfolio returns sheds light on the impact of political polarization on asset pricing. Using a three-pass regression framework with 10 principal components (PCs), the intercept of the model is estimated at 0.0045, with a standard error of 0.0004, indicating the model provides a reliable baseline for explaining portfolio returns. The estimated risk premia associated with the PC factor is -0.3114, with a variance of 0.3664, reflecting substantial variability in how partisan conflict impacts portfolio returns. Notably, while the risk premia is negative, the R_g^2 value for the PC factor is 0.5283 (Table B.4), indicating that approximately 52.8% of the variation in portfolio returns is explained by this factor. This high explanatory power highlights the relevance of partisan conflict as a systematic risk factor in understanding return patterns, particularly in an environment of increasing political polarization.

Furthermore, the results from the Standard Fama-MacBeth (FM) methodology complement these findings, reinforcing the importance of the PCI_{US} as a priced risk factor. Under the FM approach, the intercept is estimated at 0.0032 with a standard error of 0.0001, providing a similarly reliable baseline. The risk premia for PCI_{US} is estimated at 1.8075 (Table B.4), with a standard error of 0.1659, suggesting a significant and positive relationship between partisan conflict and portfolio returns under this methodology. These results contrast with the negative risk premia obtained using the Giglio and Xiu (2021) approach, underscoring the sensitivity of pricing estimates to the methodology employed. These findings strongly support the existing literature by providing a conceptual framework that differentiates between the Partisan Conflicts Index (PCI) and the Economic Policy Uncertainty Index (EPU).

azzimonti2018partisan highlights that while PCI and EPU share similar computational methodologies, they measure different dimensions of political and economic risks. Our results reflect this distinction, as the negative risk premium associated with PCI_{US} suggests that heightened partisan conflict erodes investor confidence and dampens returns.

In contrast, the positive risk premia for EPU_{US} and EPU_{States} indicate that economic policy uncertainty, though disruptive, can create opportunities that are priced into returns. The literature demonstrates that PCI and EPU can diverge under specific conditions, such as wars or national security threats. For example, during the 9/11 attacks or World War I, EPU increased sharply due to uncertainty about government policy, while PCI remained low because of bipartisan unity. This observation aligns with our finding that PCI_{US}'s negative risk premium reflects systemic inefficiencies and heightened risks during periods of political polarization, which are distinct from the broader economic uncertainty captured by EPU.

Furthermore, the literature underscores how extreme partisan conflict (high PCI) can lead to government gridlock or shutdowns, reducing the effectiveness of policies and amplifying economic risks. Our results support this notion, as the negative pricing of PCI_{US} highlights the detrimental impact of such conflicts on investor sentiment and market stability. Azzimonti (2018) also suggests that moderate levels of PCI may align with heightened EPU as investors grapple with policy uncertainty. For instance, during debates over the debt ceiling, Obamacare, and the tax expirations of 2012, disagreements between parties led to elevated uncertainty about economic policies. Our results align with this interpretation, as both EPU_{US} and EPU_{States} exhibit positive risk premia, indicating that these uncertainties are priced into returns when partisan conflict is moderate.

An important distinction noted in the literature is that PCI is unaffected by monetary policy, whereas EPU may respond to changes such as Federal Reserve actions. This reinforces our findings, where PCI represents a unique dimension of risk that investors price separately from the broader economic uncertainty captured by EPU.

Moreover, our analysis highlights the higher risk premium for EPU_{States} compared to EPU_{US}, suggesting a more pronounced impact of localized economic uncertainty on asset pricing. The literature supports this by emphasizing that PCI_{US} captures broader systemic risks tied to political polarization, which can amplify the pricing of localized uncertainties, as reflected in EPU_{States}. The distinctions outlined in the literature provide a theoretical foundation for interpreting the interplay between PCI and EPU. Specifically, they justify the observed differences in risk premia and variances in our results, as well as the broader narrative that political and economic uncertainties impact asset pricing in unique and sometimes divergent ways. This reinforces the importance of analysing these factors together, as their combined effects offer a more comprehensive view of the risks faced by investors. By integrating these insights into our discussion, we strengthen the argument that PCI and EPU capture complementary but distinct dimensions of uncertainty. Their differential pricing dynamics reflect varying investor perceptions of risk under different political and economic conditions.

Next, we examine the updated results for the Economic Conditions Indicator ($ECON_{US}$) in the U.S. (Table B.4). In the standard FM estimation, $ECON_{US}$ shows a highly significant positive intercept of 0.0040 ($p < 0.001$), indicating a baseline positive return that is consistent with the other models. The FM risk premia estimate of 2.6936 (with a standard error of 0.2288) suggests a strong relationship with economic conditions ($p < 0.01$). This result underscores the sensitivity of portfolios to changes in economic indicators such as economic growth, inflation, and monetary policy, confirming the importance of economic conditions in influencing asset pricing.

Additionally, using the three-pass methodology with 10 PCs, the intercept remains stable at 0.0045 (with a standard error of 0.0006), while the risk premia estimate decreases slightly to -0.0574, with a standard error of 0.3477. This decrease suggests that the impact of economic conditions on portfolio returns is less pronounced when accounting for the higher-dimensional variation captured by the principal components. However, the variation in the risk premia highlights the complexity of modelling economic conditions and their effects on investment returns.

These findings underscore the significant impact of both economic policy uncertainty (EPU_{US}) and economic conditions ($ECON_{US}$) in the U.S. on portfolio returns, particularly for firms with strong ESG characteristic. Moreover, the results resonate with the methodology proposed by Giglio, Kelly, and Stroebel (2021), which emphasizes the importance of incorporating climate-related risks and policy uncertainty into asset pricing models. This approach is further supported by Sheng, Gupta, and Çepni (2022), who demonstrate that increased uncertainty exacerbates the adverse effects of climate risks on economic activity and investment returns.

In summary, both EPU_{US} and $ECON_{US}$ significantly affect portfolio returns, underscoring the importance of macroeconomic indicators in portfolio management decisions. These findings provide valuable insights for investors seeking to navigate economic uncertainties and capitalize on opportunities, particularly in the energy sector and with regard to ESG considerations.

2.5.3 Fama-French Factors

Table 5 presents the estimated risk premia associated with the Fama-French factors, obtained through the Fama-MacBeth two-pass regression model and the three-pass estimation method proposed by Giglio and Xiu (2021). The analysis centers on two prominent models: the Fama-French Three-Factor Model (FF3), which includes the Market (MKT), Size (SMB), and Value (HML) factors, and the Fama-French Five-Factor Model (FF5), which adds Profitability (RMW) and Investment (CMA) to the original three factors. The dataset spans a period of 277 months and is based on 20 test portfolios, specifically designed to capture the characteristics of U.S. energy firms, including those with high energy dependence and varying levels of ESG performance.

[**Table B.5 around here**]

In the Fama-MacBeth two-pass regression model estimates for the Fama-French risk factors (Table B.5), the intercept remains consistently positive, approximately 0.0040 for the Fama-French Three-Factor Model (FF3) and 0.0042 for the Five-Factor Model (FF5). This suggests a stable baseline return across all portfolios, which could reflect a general market equilibrium not entirely captured by the included factors. The risk premia estimates for the individual factors reveal considerable variability, emphasizing their distinct contributions to portfolio returns.

Specifically, the market factor (MKT) exhibits a robust positive risk premium of 5.0783, with a standard error of 0.3428, underscoring the substantial compensation investors demand for bearing systematic market risk. The size factor (SMB) shows a modest positive risk premium of 0.3206, suggesting a mild preference for smaller firms, which aligns with the historical tendency of small-cap stocks to outperform their larger counterparts during certain market conditions. In contrast, the value factor (HML) demonstrates a significantly positive risk premium of 9.9083, reinforcing the consistent outperformance of value stocks relative to growth stocks, a phenomenon often attributed to the market's undervaluation of financially stable, lower-growth firms.

The empirical results derived from the Three-Pass Regression methodology applied to the Fama-French Five-Factor Model (FF5) provide further granularity (Table B.5). The intercept remains stable at approximately 0.0045, consistent with the findings from the FF3 model and reaffirming the presence of an unexplained positive baseline return.

Interestingly, the market factor (MKT) presents a negative risk premium of -0.0099, accompanied by a reduced standard error of 0.1426. This divergence suggests that the 3PRF methodology, which leverages principal components to account for latent systematic factors, captures different dynamics in market risk compared to traditional FM estimation.

The size factor (SMB) and value factor (HML) display more moderate risk premia under the 3PRF method, with estimates of 0.1761 and 0.2774, respectively, alongside reduced standard errors, indicating improved precision in their estimation. The additional factors introduced in the FF5 model, profitability (RMW) and investment (CMA), exhibit significant variability. For instance, RMW shows a negative risk premium of -2.9438 in the FM model, which moderates substantially to -0.1612 under the three-pass methodology, suggesting that profitability may not be a consistent driver of returns in this sector. Meanwhile, CMA demonstrates a notable positive risk premium of 8.4491 in the FM model, which decreases to 0.3254 under the three-pass methodology, reflecting the sensitivity of investment-related returns to model specifications.

These findings indicate that while the Fama-French factors capture critical dimensions of risk relevant to broader markets, their explanatory power for U.S. energy firms with strong ESG characteristics is somewhat limited. The consistently positive intercepts across both models suggest that significant aspects of returns remain unexplained, pointing to the need for additional factors that account for sector-specific risks, such as regulatory changes, technological innovation, or environmental policies.

The strong positive risk premium for HML aligns with the historical outperformance of value stocks, emphasizing their role as a critical driver of returns. In contrast, the variability in MKT and SMB estimates highlights their sensitivity to methodological changes and prevailing market conditions, necessitating cautious interpretation in practical applications. These findings underscore the importance of considering both traditional equity factors and unique sectoral attributes when analysing portfolios in the energy sector.

Moreover, the three-pass estimation method proposed by Giglio and Xiu (2021) refines risk premium estimates by incorporating a richer structure of principal components, effectively capturing latent systematic risks that might otherwise be overlooked. This nuanced approach is particularly beneficial for specialized portfolios, as it provides deeper insights into risk premia dynamics. The methodology's ability to adjust for latent factors suggests its potential for broader applications in asset pricing models, especially in environments characterized by high complexity or sector-specific nuances.

Overall, the application of the Fama-French frameworks to U.S. energy firms with strong ESG characteristics highlights the necessity of integrating both traditional equity factors and sector-specific considerations into asset pricing models. These findings offer valuable insights for investors and portfolio managers aiming to optimize risk-adjusted returns in energy-focused investment strategies, while also addressing the unique challenges and opportunities posed by ESG considerations and the evolving energy landscape.

2.5.4 U.S. State Level Factors

A significant contribution of our research lies in the integration of a climate change indicator at the state level into our asset pricing model. This addition reflects the heterogeneity in states' abilities to address the policy void created by federal inaction on climate change. While some U.S. states have implemented proactive climate policies and regulatory measures, others remain less equipped to manage the associated risks. This variability necessitates a more granular approach to risk measurement, one that goes beyond a uniform nationwide perspective and accounts for the nuanced impact of state-level factors on investment dynamics. The challenge is not solely in isolating state-specific risks from broader national trends but in recognizing and quantifying the unique insights state-level information provides. By incorporating state-level transition risk into our analysis, we underscore its critical role in optimizing portfolio returns and enhancing the understanding of how localized climate policies and economic conditions influence financial markets. This approach highlights the increasing relevance of geographically disaggregated data in investment decision-making and risk management, particularly in the context of climate-related financial risks. The primary findings derived from state-level factors are presented in Table 6. These results are obtained using the Fama-MacBeth two-pass regression model and the three-pass regression methodology introduced by Giglio and Xiu (2021). Together, these methods allow for a comprehensive examination of how state-level transition risks interact with broader market forces to shape portfolio outcomes.

[**Table B.6 around here**]

Temperature Anomalies

Based on the results presented in Table B.6, the integration of temperature anomalies ($Tanomalies$) at the U.S. state level into the asset pricing model provides valuable insights, addressing a key research question. The findings indicate that temperature anomalies constitute a significant risk factor that U.S. firms and investors should incorporate into their risk assessments and portfolio management strategies. Specifically, higher average temperature anomalies in degrees Fahrenheit are associated with increased investor demand for higher portfolio returns, reflecting the compensation required for bearing the associated climate risk.

The results show that the intercept remains positive and statistically significant across all models, including both the Standard Fama-MacBeth (FM) model and the Giglio and Xiu (2021) three-pass regression methodology. This indicates a consistent baseline return across portfolios, irrespective of model specifications. Notably, the risk premium for $Tanomalies$ differs substantially between the two methods. In the Standard FM model, the risk premium is estimated at 4.2121, whereas the Giglio and Xiu methodology (using 10 principal components) produces a more refined estimate of 0.1422 with significantly reduced standard errors. These differences suggest that the more sophisticated three-pass regression methodology captures nuanced dynamics of climate risk with greater precision.

Temperature anomalies are identified as a critical source of climate-related risk, particularly for the energy sector. Extreme temperatures can disrupt energy production, distribution, and demand, thereby impacting the operational performance and costs of U.S. firms. Investors demand higher premiums to compensate for these risks, particularly in portfolios with lower ESG rankings (e.g., portfolio 1). Conversely, portfolios with higher ESG rankings (e.g., portfolio 20) tend to exhibit lower sensitivity to $Tanomalies$, likely due to better risk management practices and proactive measures to mitigate climate-related risks.

These results underscore the utility of integrating state-level climate risk factors into financial models. The detailed outputs from regression analyses provide a nuanced understanding of how such factors influence portfolio returns and asset pricing. The findings demonstrate that temperature anomalies as a state-level risk factor significantly affect the portfolio performance of energy and energy-dependent firms, highlighting the importance of localized climate data in assessing financial risks. At the same time, our state-level estimates are consistent with international evidence that equity markets price climate risk once the climate signal is separated from macro-financial components, reinforcing the view that careful identification is crucial for interpreting climate-related premia (Cassola, Morana, and Ossola (2024)).

These findings have several implications. For risk management, energy firms and investors may need to consider temperature anomalies as a significant risk factor when managing portfolios. For investment strategy, incorporating climate-related risk factors, such as temperature anomalies, could enhance portfolio performance. Furthermore, insights from this analysis could inform policy decisions related to climate resilience and energy and highly dependent energy sector planning.

Overall, the positive and significant risk premia estimates for $Tanomalies$ underscore their substantial impact on the portfolio performance of U.S. firms. The findings emphasize the importance of integrating climate-related risk factors into investment strategies and risk management practices. Additionally, the observed relationship between ESG performance and the influence of temperature anomalies on portfolio returns reinforces the value of incorporating ESG considerations into investment analysis. Portfolios with higher ESG scores demonstrate greater resilience to climate-related risks, as evidenced by their reduced sensitivity to $Tanomalies$. These results highlight the necessity for investors to account for both ESG performance and climate risks in assessing the risk-return profiles of their investments, especially in sectors vulnerable to climate change

Macroeconomic State Level Factors

Our analysis of economic policy uncertainty at the state level (EPU_{States}) reveals significant insights into its impact on portfolio performance. Table B.6 shows that the intercept remains consistently positive and statistically significant across models, ranging from 0.0032 in the Standard Fama-MacBeth (FM) model to 0.0045 in the Giglio and Xiu (2021) methodology. This result reflects a stable baseline level of portfolio performance that is unaffected by the modelled factors, underscoring the robustness of the underlying return structure.

The risk premia for EPU_{States} exhibit positive values across both methodologies, with 1.5217 in the Standard FM model and a more modest 0.2241 using the three-pass methodology. This positive risk premium implies that heightened economic policy uncertainty at the state level leads to increased compensation demands from investors. These findings align with Baker et al. (2016), who highlighted the adverse effects of elevated policy uncertainty on investment and stock returns. At the state level, economic policy uncertainty captures local economic conditions and regulatory landscapes, which vary across regions and can significantly impact regional investments.

Changes in EPU_{States} often signal shifts in investor sentiment and market expectations, influencing portfolio allocation decisions. Understanding the timing and implications of these changes can provide investors with strategic advantages, enabling them to manage associated risks more effectively and optimize returns.

Similarly, our analysis of state-level economic conditions ($ECON_{States}$) provides comprehensive insights into their influence on portfolio performance. As shown in

Table B.6 the intercept remains consistently positive, fluctuating slightly from 0.0041 (Standard FM model) to 0.0045 (Giglio and Xiu methodology). These results indicate a stable underlying return level, reinforcing the reliability of the model.

The risk premia for $ECON_{States}$ range from 2.8582 in the Standard FM model to 0.1700 in the Giglio and Xiu methodology. These estimates suggest that stronger economic conditions at the state level positively impact portfolio returns, likely driven by improved corporate earnings, heightened investor confidence, and favourable regional dynamics. Conversely, adverse economic shocks, including climate-related shocks, are associated with higher risk premiums, consistent with theoretical expectations (Chen, Roll, and Ross, 1986). This underscores the critical role of state-level economic health in shaping investment opportunities and portfolio performance.

State-level economic conditions ($ECON_{States}$) reflect regional economic fundamentals, influencing local market dynamics and investment prospects. Investors are likely to favour regions with stronger economic performance, anticipating higher returns from such areas. For instance, robust economic growth in specific states can benefit industries such as real estate, retail, and services, prompting shifts in portfolio sector allocations. Conversely, economic downturns or shocks increase risk premiums, reflecting heightened uncertainty and potential losses.

The variability in risk premia estimates, suggests that the impact of economic conditions indicator at the state level on portfolio performance is complex and multifaceted. We cab state that $ECON_{States}$ reflect the economic health across states, influencing local market dynamics and investment opportunities. Investors might favour regions with stronger economic fundamentals, anticipating higher returns from such areas. Strong economic conditions in specific states can benefit particular industries such as real estate, retail, and services. This influence can affect portfolio sector allocations, making it advantageous to consider regional economic conditions when making investment decisions. Understanding state-level economic conditions helps investors manage risk exposures and optimize returns.

In conclusion, state-level factors such as EPU_{States} and $ECON_{States}$ play a pivotal role in shaping portfolio returns. By incorporating these factors into asset pricing models, investors can better understand and navigate the risks and opportunities associated with regional economic variations. The findings underscore the necessity of a nuanced approach to modelling and interpreting the effects of economic conditions and policy uncertainty on portfolio performance. This approach not only enhances portfolio optimization but also supports more effective risk management in an increasingly complex economic landscape.

2.6 Robustness

In this section, we explore the influence of state-level climate risk factors - both physical and transition risks - to confirm the previous results that address the following research question: "How does the implementation of climate policies across diverse U.S. states influence national-level transition risks, and are these risks adequately reflected in market valuations of U.S. firms?". This approach demonstrates how these factors are priced in the cross-section of returns for U.S. energy sector firms, providing a realistic assessment of market valuation accuracy in relation to climate risk integration.

2.6.1 Comprehensive Climate Physical Risk Factor

We create a comprehensive climate physical risk indicator for 38 U.S. states from March 2000 to March 2023, we utilized a combination of temperature anomalies and the number of natural disasters occurring in each state on a monthly basis. The natural disaster data was sourced from the Federal Emergency Management Agency (FEMA) (2024) database, detailing the frequency and start dates of various natural disasters across 38 U.S. states.

[**Figure B.3 around here**]

Figure B.3 presents a heatmap illustrating the annual number of natural disasters for each state from 2000 to 2023. This visual representation allows us to observe trends and variations in the frequency of natural disasters across the states over the specified period. Notably, there has been a marked increase in the total number of natural disasters during the last decade, particularly in states such as Georgia, Illinois, Indiana, Kansas, and Maryland. This trend indicates a growing vulnerability and frequency of climate-related events in these regions.

The data highlights Texas as the leading state in terms of the total number of natural disasters, followed closely by Oklahoma and Missouri. These states have experienced a disproportionately high number of natural disasters, underscoring their susceptibility to climate extremes and the need for robust disaster preparedness and mitigation strategies.

We first processed the natural disaster data to aggregate the number of disasters by state and by month. Any months with no recorded disasters were assigned a value of zero to maintain the continuity of the dataset. Concurrently, temperature anomaly data was organized similarly by state and month to ensure alignment with the natural disaster data.

Normalization of the two datasets was then performed using min-max scaling, ensuring that each variable ranged from 0 to 1, which allowed for the combination of these two disparate datasets. Specifically, the number of natural disasters and temperature anomalies were normalized independently to facilitate their integration into a single composite indicator.

We calculated the climate physical risk score for each state and month by employing a weighted sum of normalized values, prioritizing the influence of natural disasters and temperature anomalies on physical climate risk. We assigned a weight of 0.7 to the normalized number of natural disasters, recognizing their immediate and severe impact, and a weight of 0.3 to the normalized temperature anomalies to account for their gradual yet significant effects. The resulting scores, which range from 0 to 100, quantify the level of climate physical risk, with higher scores indicating increased risk within a specific state during the given time period.

The final climate physical risk indicator provides a robust monthly measure of climate-related risks for each state, combining historical climatic deviations with the frequency of impactful natural events. This indicator serves as a valuable tool for assessing and comparing the climate-related risks faced by different states over the specified time period, aiding in the development of targeted mitigation and adaptation strategies.

Next, we delve into the risk premia associated with state-specific climate risk factors, as detailed in table B.11. These estimated risk premia are derived using the methodology proposed by Giglio and Xiu (2021). For each climate risk factor, we concentrate on the estimates of the market price of risk (λ) and the proportion of its time-series variation attributable to each of the latent factors.

[**Table B.7 to Table B.8 around here**]

The analysis covers a period of 277 months, utilizing 20 test portfolios to identify the target factor linked to each of the 38 distinct U.S. states. This comprehensive approach allows for a nuanced understanding of how climate risk factors impact state-specific risk premia and highlights the variation in the market price of risk across different states, using a maximum of 10 PCs as suggested by Giglio and Xiu (2021).

The analysis reveals that the R_g^2 values for individual factors generally increase with the inclusion of more principal components (PCs). This improvement signifies that additional PCs contribute significantly to explaining the variance in returns attributed to state-level climate anomalies. For example, in Alabama, the R_g^2 values for each factor rise from 0.035319 to 0.056144, underscoring the model's enhanced explanatory power with the incorporation of more PCs.

The variability in risk premia across states reflects the diverse impact of climate risks on portfolio performance. States like Arkansas, with a high FM risk premia of 6.5426 and a standard error of 0.6665, contrast sharply with Arizona, which presents a lower FM risk premia of 1.2232 with a standard error of 0.3451. This disparity highlights the different degrees of climate risk exposure across states, indicating that investors demand higher returns for greater perceived risks.

Moreover, the positive and statistically significant intercept values across all states and models suggest a consistent baseline return not captured by the risk factors alone. In Alabama, for instance, the intercept peaks at 0.0047 when utilizing 6 to 8 PCs, indicating a stable underlying return amidst varying climate risks.

The detailed state analysis, summarized in Table B.8, reinforces the pricing of climate risks into investment portfolios. Each state shows a positive and significant risk premium, such as California's 3.5048, reflecting its vulnerability to wildfires and droughts, and Illinois' 7.9214, highlighting the substantial returns demanded by investors for climate risks.

Nebraska and Minnesota exhibit exceptionally high-risk premia, pointing to the severe climate risks priced into their markets. Conversely, Wisconsin's significant risk premium of 8.6153 emphasizes the crucial role of climate risks in shaping investment returns in the state.

These findings confirm that climate risk factors are indeed priced into portfolio returns across various U.S. states, with investors requiring higher returns to compensate for these risks. The analysis also shows that portfolios with higher ESG scores, which indicate better environmental performance, tend to be less sensitive to climate risks, underscoring the importance of integrating ESG factors into investment strategies.

Overall, the results reinforce prior evidence that state-level climate risks shape investment decisions, with substantial and positive risk premia indicating that investors recognize and price these exposures in their portfolios. This interpretation is consistent with Kruttli, Tran, and Watugala (2025), who show that extreme weather events, particularly hurricanes, generate material firm-level uncertainty that can be decomposed into incidence uncertainty (the probability of being affected) and impact uncertainty (the severity conditional on being hit)[18]. Taken together, our state-specific results complement this evidence by suggesting that, even when climate risks are priced on average, markets and firms may still struggle to efficiently incorporate and adapt to novel

[18]Kruttli, Tran, and Watugala (2025) document pronounced increases in option-implied volatility for firms in landfall regions both before and after impact, evidence that investors initially underestimate uncertainty, while the attenuation of this under-reaction after Hurricane Sandy points to a learning effect. Importantly, although hurricanes are largely idiosyncratic shocks, the authors demonstrate that they affect expected returns through both cash-flow and discount-rate channels, and that hurricane-related discussions persist in earnings calls long after landfall, highlighting the durability of climate-induced uncertainty.

physical risks, reinforcing the value for portfolio managers of integrating granular, state-level climate risk assessments alongside ESG considerations to improve risk management and optimize risk, adjusted returns amid rising climate variability.

For example, Jung et al. (2024) confirm that U.S. counties with high exposure to physical climate risks experience disproportionately larger declines in stock returns following severe natural disasters. However, a notable limitation of their research is its reliance on the extent to which the market itself prices climate risks, raising the question of whether equity market investors fully account for such risks. Our findings support their conclusions by providing evidence that physical risk factors, such as natural disasters and temperature anomalies, have measurable impacts on portfolio returns. This further substantiates the argument that equity markets indeed price physical climate risks, highlighting the necessity of factoring these risks into investment strategies as climate-related events become more frequent and severe.

2.6.2 Climate Policy Index

In this section, we analyse the risk premia linked to a novel risk factor quantifying climate transition risk, specifically focusing on climate policies adopted across various U.S. states. This analysis utilizes the climate policy index[19] proposed by Bergquist and Chris Warshaw (2023), which aggregates data from 25 individual policies to construct a comprehensive index reflecting state-level climate policy actions from 2000 to 2020. According with the authors (Bergquist and Chris Warshaw (2023)) this period marks a critical phase during which states enacted the majority of their climate-related policies, making it a focal point for our study.

The climate policy index illuminates variations in policy adoption and design across states, offering a richer perspective than single-policy analyses typically provide. By compiling a detailed dataset, Bergquist and Chris Warshaw (2023) captures nuances in the adoption and specific designs of 25 widely implemented policies aimed at reducing greenhouse gas emissions, promoting cleaner energy production, and enhancing energy efficiency across multiple states.

Due to data limitations, we constrain our analysis time-frame from March 2000 to December 2020. Given the annual nature of the indicator, we assume the same value for each month within a given year, under the reasonable assumption that climate policies

[19]The authors Bergquist and Chris Warshaw (2023) employ various types of policy data-ordinal, dichotomous, and continuous - as inputs for a Bayesian factor analysis model. This method is utilized to estimate the stringency of state climate policy regimes, which serves as the foundation for creating the climate policy index.

do not change monthly at the U.S. state level. Our methodology, following Giglio and Xiu (2021), focuses on identifying statistically significant state climate transition risk factors. The statistically significant results of this comprehensive analysis are detailed in table 13, providing insights into how state-specific climate policies are factored into market valuations and the associated risk premia.

[**Table B.9 around here**]

The analysis of the climate transition risk factor, which measures the impact of climate policies adopted in each state, reveals significant insights across various U.S. states. We focus on the risk premia, standard errors, cross-sectional R^2 values, and the suggested number of factors for each state (Table B.9). The findings highlight the importance and statistical significance of the climate transition risk factor in the economic landscape of these states.

For Alabama, the Fama-MacBeth (FM) risk premia estimate is 1.0328 with a standard error of 0.0729, indicating a strong and statistically significant risk premium. Using the three-pass method with four principal components (PCs), the risk premia estimate is 0.7799 with a higher standard error of 0.4464, reflecting greater variability. When increasing to ten PCs, the risk premia estimate is 0.8723 with a standard error of 0.4322. The cross-sectional R^2 values range from 0.2165 to 0.6992, with the R_g^2 values improving from 0.7817 to 0.9083 as more PCs are included, suggesting a robust model fit with additional PCs. The positive risk premia indicates that investors require compensation for exposure to climate transition risks in Alabama, reflecting the perceived economic impact of climate policies in this state.

Arkansas presents a similar scenario the FM risk premia is 0.8332 with a standard error of 0.0700. The three-pass method yields a risk premia of 0.8074 with a standard error of 0.4262 when using four PCs, and 0.6093 with a standard error of 0.3774 when using ten PCs. The R^2 values increase from 0.2165 to 0.6992, with R_g^2 values improving from 0.8411 to 0.9437, highlighting the model's robustness with more principal components. The positive risk premia for Arkansas indicates that investors perceive significant economic risks associated with the implementation of climate policies, requiring compensation for holding such investments.

For California, the FM risk premia estimate is 0.8166 with a standard error of 0.0752. The three-pass method with four PCs gives a risk premia of 0.6732 with a standard error of 0.4244, while with ten PCs, the estimate increases to 0.9173 with a standard error of 0.4144. The cross-sectional R^2 values improve from 0.2165 to 0.6992, with R_g^2 values ranging from 0.7480 to 0.8938, indicating a solid fit and the model's increasing explanatory power with more PCs. The positive risk premia in California reflect the state's aggressive climate policies and the significant economic adjustments required, thus leading investors to demand higher returns for these risks.

In Colorado, the FM risk premia is estimated at 0.7338 with a standard error of 0.0691. Using the three-pass method, the risk premia is 0.7567 with a standard error of 0.4388 when using four PCs, and 0.8280 with a standard error of 0.3682 when using ten PCs. The cross-sectional R^2 values range from 0.2165 to 0.6992, with R_g^2 values showing significant improvement from 0.8868 to 0.9630 as more PCs are incorporated, highlighting the increasing robustness of the model. The positive risk premia indicate that investors in Colorado also seek compensation for the economic uncertainties and adjustments related to climate transition policies.

In conclusion, these findings underscore the economically meaningful, and heterogeneous, pricing of climate transition risk across U.S. states, reinforcing our earlier results. The risk premia estimated via both the Fama–MacBeth approach and the three-pass methodology Giglio and Xiu (2021) are predominantly positive and statistically significant, indicating that investors require compensation for exposure to transition-policy risk and the associated uncertainty surrounding future regulation and local adjustment costs. This interpretation is closely aligned with recent work that frames transition risk through the lens of stranded assets and argues that exogenous transition-risk shocks are often triggered by major public information releases and political decisions, generating broad repricing and financial instability rather than merely reflecting movements in simple policy proxies such as carbon prices Meinerding, Schüler, and Zhang (2024). Finally, the increase in R^2 and R_g^2 as additional principal components are included further supports the robustness and explanatory power of our empirical specification, suggesting that a richer factor structure improves the measurement and transmission of state-level transition risk into expected returns.

2.6.3 Normalized Climate Transition Risk Index (NCTRI)

In this section, we construct a Normalized Climate Transition Risk Index (NCTRI) at the state level, drawing on the work of Campiglio et al. (2025). The authors analyze climate-related central bank communication using a novel dataset [20] comprising 35,487 speeches delivered by 131 central banks between 1986 and 2023, including U.S. Federal Reserve Banks. Their study applies natural language processing (NLP) techniques to identify and trace the evolution of key climate-related narratives, with a focus on two dimensions: green finance and climate-related financial risks. Campiglio et al. (2025)

[20] For more details on the CBS Speeches Explorer, visit https://cbspeeches.shinyapps.io/explorer/.

further investigate the impact of central bank communication on equity asset prices and find that, compared to firms with worse environmental scores, greener firms exhibit positive returns associated with the frequency and salience of climate-related speeches, especially when the dominant topic revolves around climate-related financial risks. Their results, derived from both portfolio-level analysis (for the U.S.) and firm-level data (from 41 countries), highlight that central bank public communication strategies are primarily driven by underlying institutional factors rather than direct exposure to climate-related risks. Notably, their findings demonstrate that the equity returns of 'green' firms outperform those of 'dirty' firms during periods of heightened climate-related communication by central banks, emphasizing the nuanced and significant role of central bank discourse in climate finance.

This evidence aligns with the findings of Ardia et al. (2023), who argue that investors exhibit a willingness to pay a premium for greener firms, thereby accepting lower expected returns. However, the negative and statistically significant coefficient associated with climate-related communication suggests that markets may still perceive discussions on climate-related risks as potentially detrimental to economic activity, reinforcing the need for a deeper understanding of climate risk in financial markets.

Building on this foundation, we create a Normalized Climate Transition Risk Index (NCTRI) at a monthly frequency, leveraging the comprehensive database provided by Campiglio et al. (2025). Our analysis focuses exclusively on U.S. Federal Reserve Banks [21], encompassing speeches delivered by the following institutions between March 1, 2000, and March 1, 2023.

To ensure sufficient data for robust estimation, we analyze the entire set of U.S. central bank speeches rather than restricting the analysis to only climate-related speeches, as the latter would have resulted in an insufficient sample size. We identify occurrences of key climate-related expressions following Campiglio et al. (2025)[22].

The NCTRI[23] is constructed by aggregating the monthly frequency of climate-related

[21] U.S. Federal Reserve Banks considered in this analysis: Board of Governors of the Federal Reserve, Federal Reserve Bank of Atlanta, Federal Reserve Bank of Boston, Federal Reserve Bank of Chicago, Federal Reserve Bank of Cleveland, Federal Reserve Bank of Dallas, Federal Reserve Bank of Kansas City, Federal Reserve Bank of Minneapolis, Federal Reserve Bank of New York, Federal Reserve Bank of Philadelphia, Federal Reserve Bank of Richmond, Federal Reserve Bank of San Francisco, and the Federal Reserve Bank of St. Louis.

[22] Environment-related keywords: "climate change," "green finance," "green," "climate finance," "sustainable," "investment," "transition," "energy," "carbon," and "financial sustainability." The narrative emerging from it is more strongly aligned with a prudential – rather than promotional – perspective, as it focuses on how climate-related dynamics might have disruptive impacts on financial markets and the strategies to manage these risks.

[23] The Climate Frequency Index (CFI) is the sum of climate-related keywords in each speech, defined as $CFI_i = \sum_{k=1}^{n} \mathbf{I}(w_{k,i})$, where $\mathbf{I}(w_{k,i})$ indicates the presence of the k-th climate keyword in the i-th

expressions across speeches and normalizing the count by speech length (expressed per 100 words) to account for variations in speech length. This normalization ensures that longer speeches do not disproportionately influence the index, making it a more accurate reflection of the relative emphasis placed on climate-related topics. The resulting NCTRI provides a quantitative measure of the evolving focus on climate transition risks in U.S. central bank communication over time. Higher values of the NCTRI reflect a greater emphasis on climate transition risks, while lower values suggest minimal discussion of climate-related topics. The NCTRI values range from near 0 (low mention frequency) to over 18 mentions per 100 words (high intensity of climate-related mentions). Consequently, values close to zero indicate minimal climate-related discourse, while higher values signify increased emphasis on climate-related financial risks and green finance.

The inclusion of the NCTRI in our robustness checks allows us to assess potential shifts in investor sentiment and risk premia arising from changes in climate-related discourse by U.S. central banks. By incorporating the NCTRI, we capture the dynamic evolution of climate-related discussions and its potential implications for U.S. firms' portfolio returns over time, providing a more nuanced understanding of the role of climate-related communication in influencing asset prices.

[**Figure B.4 around here**]

Figure B.4 illustrates the evolution of the NCTRI from March 2000 to March 2023, highlighting key trends in climate-related discourse by U.S. central banks. The figure reveals a distinct shift in climate discourse over this period, with minimal attention to climate transition risks prior to 2008. This period of low NCTRI values suggests that climate-related risks were not a primary concern for U.S. central banks during the early 2000's. However, a gradual increase in climate-related mentions emerges in the aftermath of the 2008 global financial crisis, signalling a growing awareness of climate-related financial vulnerabilities.

Significant policy milestones appear to coincide with fluctuations in the NCTRI. A notable upward trend begins in 2009 following the passage of the American Recovery and Reinvestment Act (ARRA), which directed significant investments toward clean energy and renewable technologies, prompting increased attention to climate-related financial risks. This upward trajectory continues until 2015, when the Paris Agreement led to a marked increase in climate-related mentions by U.S. central banks. This period from

speech. To adjust for speech length, the Normalized Climate Frequency Index (NCFI) is calculated as $NCFI_i = \left(\frac{CFI_i}{\text{wordcount}_i}\right) \times 100$, where wordcount_i is the word count. The monthly NCTRI is the sum of NCFI values for all speeches in a month, $NCTRI_m = \sum_{i \in M_m} NCFI_i$.

2015 to 2022 is characterized by sustained higher NCTRI values, reflecting heightened discourse on climate risk management, transition scenarios, and regulatory adaptation.

The subsequent U.S. withdrawal from the Paris Agreement in June 2017 led to a brief stagnation in climate-related discourse, as reflected in the temporary decline in NCTRI values. However, renewed momentum is observed following the 2021 U.S. rejoining of the Paris Agreement, which revived discussions on climate-related financial vulnerabilities and transition risks. Another sharp increase in NCTRI values is evident following the passage of the Inflation Reduction Act (IRA) in August 2022, which brought major climate investments and reinforced the role of climate-related policy in shaping financial system dynamics.

Despite some fluctuations, particularly after COP26 in 2021, the sustained higher NCTRI values (ranging between 8 and 12 mentions per 100 words) underscore the growing prominence of climate-related considerations in U.S. central bank discourse. These peaks in the NCTRI align closely with major global climate events and policy changes, highlighting the responsiveness of U.S. central banks to evolving climate-related developments and the increasing integration of climate considerations into financial stability assessments.

The NCTRI serves as a robust indicator of climate-related discourse, enabling us to trace the progression of climate-related awareness within U.S. central bank communication and to identify key periods of heightened engagement. By capturing both the magnitude and frequency of climate-related narratives, the NCTRI provides critical insights into the role of climate communication in shaping market expectations and investor sentiment over the past years.

[**Table B.10 around here**]

Table B.10 presents the risk premia estimates associated with the newly constructed Normalized Climate Transition Risk Index (NCTRI) and a set of tradable and non-tradable factors employed in our research. The risk premia are estimated using the methodology proposed by Giglio and Xiu (2021), which applies a three-pass regression filter to extract latent factors and their corresponding market prices of risk (λ). To ensure robustness, we compare these estimates with results obtained using the standard Fama-MacBeth (FM) methodology, providing a comprehensive evaluation of the NCTRI's impact on portfolio returns.

For each climate risk factor, we focus on two critical dimensions: (i) the market price of risk and (ii) the proportion of time-series variation attributable to the latent factors. The analysis spans a period of 277 months, from March 2000 to March 2023, and employs 20 test portfolios to capture the impact of the NCTRI across 38 distinct

U.S. states. By incorporating a broad set of portfolios and accounting for state-level heterogeneity, this approach offers a nuanced understanding of how the NCTRI factor influences U.S. firms' portfolio returns over time. Following the recommendation by Giglio and Xiu (2021), we use a maximum of 10 principal components (PCs) to capture the latent structure of climate-related communication and its potential effects on asset prices.

The results, presented in Table B.10, highlight notable differences between the estimates derived from the three-pass methodology and those obtained through the standard Fama-MacBeth (FM) approach. This comparison provides insights into the consistency and significance of climate-related risk factors in explaining U.S. firm portfolio returns across different models and estimation techniques.

The analysis yields mixed evidence on whether the NCTRI is priced into U.S. firms' portfolio returns over the examined period. Under the standard Fama-MacBeth (FM) methodology, the risk premia estimate is -3.5745 with a standard error of 0.3130, suggesting a statistically significant negative premium associated with the NCTRI factor. This result indicates that U.S. firms' portfolio returns exhibit negative compensation for exposure to climate-related transition risks. Consistent with findings by Ardia et al. (2023), this negative and statistically significant coefficient suggests that markets may still perceive climate-related communication and transition risks as potentially detrimental to economic activity. This reinforces the notion that climate-related discourse by central banks may introduce uncertainty, contributing to negative pricing effects. These findings align with prior research demonstrating the significant impact of climate-related news and events on the returns of green and dirty portfolios, as well as stock market indices (Pástor, Stambaugh, and Taylor (2022), Ardia et al. (2023), M. D. Bauer, Offner, and Rudebusch (2023); Bua et al. (2024)). Such studies highlight how climate-related disclosures, policy announcements, and climate transition risks can generate heterogeneous pricing responses, influencing the risk-return profiles of firms across different environmental performance categories.

In contrast, when applying the three-pass methodology by Giglio and Xiu (2021), which accounts for latent factors, the risk premia estimate is -0.1519 with a standard error of 0.2171, indicating that the estimated premium is not statistically significant in this framework. This result aligns with the findings of Campiglio et al. (2025), who demonstrate that central bank public communication strategies are primarily driven by underlying institutional factors rather than direct exposure to climate-related risks. Their results, derived from both portfolio-level analysis (for the U.S.) and firm-level data (from 41 countries), suggest that exposure to climate-related risks is not a dominant driver of central bank climate-related communication, with only carbon intensity playing a minor role in shaping discourse.

The weaker and less robust NCTRI signal under the three-pass methodology suggests that much of the climate-related variation in returns may be absorbed by latent macroeconomic or other climate risk factors. The generalized R^2 from the three-pass methodology is 0.14244, indicating that approximately 14.24% of the time-series variation in the test portfolios can be attributed to the latent factors, including the NCTRI factor. While this proportion suggests that a meaningful share of the variation is explained by these factors, the relatively moderate R^2 indicates that the NCTRI factor, while informative, is not the dominant source of return variation in these portfolios.

Overall, while the NCTRI factor appears to be priced into U.S. firms' portfolio returns under the standard Fama-MacBeth (FM) model, the three-pass methodology suggests that the pricing signal weakens when accounting for latent factors. The proportion of variation explained by these factors suggests that climate-related risks remain relevant but are not the primary driver of portfolio returns in this context. This comprehensive analysis highlights the importance of incorporating the NCTRI factor into asset pricing models to assess its impact on U.S. portfolio returns, particularly in the context of evolving climate risk considerations.

2.6.4 Firm Size and Sensitivity to State-Level Risks

As an additional robustness check, we aggregate U.S. firm returns by size instead of their ESG combined scores. This adjustment is motivated by the observation that smaller firms, due to their limited ability to reallocate operations across different states, are likely more sensitive to state-level risk factors and changes in environmental regulations. To construct size-based portfolios, we use the annual average market value (or market capitalization) of each firm, a widely recognized size metric in finance. This metric is computed as the mean market value of each firm across the entire sample period (2000–2023), providing a stable and representative measure of firm size. Firms are ranked based on their average market value and grouped into 40 portfolios using the `ntile()` function in RStudio, which ensures an even distribution of firms across portfolios.

Specifically, portfolios 1 to 20 consist of firms with the smallest market values (lowest standardized ranks), while portfolios 21 to 40 comprise firms with the largest market values (highest standardized ranks). The standardized rank for each firm is computed on a 0-1 scale within each date, ensuring consistency and comparability over time. This methodology ensures that each portfolio contains an approximately equal number of firms, except where ties in market value occur. By creating portfolios based on size, this approach enables us to investigate whether smaller firms exhibit greater sensitivity to state-level risk factors and regulatory changes compared to larger firms, providing deeper insights into the interaction between firm size and regional economic dynamics.

Table B.11 reports the risk premia associated with U.S.-wide latent factors for the first 20 test portfolios, comprising smaller firms. These factors are measured as the ratio of each factor's eigenvalue to the sum of all eigenvalues from the sample covariance matrix of these portfolios. Similarly, Table B.12 presents the risk premia estimates for test portfolios 21 to 40, which consist of larger firms. By comparing these tables, we gain valuable insights into how firms of different sizes respond to state-level risk factors and whether size amplifies or mitigates sensitivity to such risks. The first column in each table corresponds to the intercept, representing the zero-beta rate, while the subsequent columns detail the estimated risk premia for each principal component. For consistency, our analysis focuses on the first 10 principal components, capturing the most significant dimensions of variation in the data. The dataset spans 277 months, leveraging a total of 40 test portfolios to provide a robust framework for understanding the factor-driven variation in returns. These results allow us to explore whether firm size influences the extent to which U.S.-wide latent factors and state-level risks impact portfolio performance.

[Table B.11 and Table B.12 around here]

In general, small firms exhibit higher risk premia across most factors (Table B.11 and Table B.12), including climate risk factors, which can be particularly impactful for these firms. For instance, in the CPU model, the risk premium for small firms is 1.5724 under the Standard Fama-MacBeth Model and 0.3724 using the methodology of Giglio and Xiu (2021), whereas for larger firms, the corresponding values are 0.6649 and 0.2742, respectively. These findings suggest that smaller firms are more sensitive to climate risk factors, requiring a higher premium to compensate for the risks associated with climate change.

One reason for this heightened sensitivity is that smaller firms often have less flexibility to reallocate their operations to states or regions with more favourable climate policies and lower associated risks. Unlike larger firms, which may have the resources and operational scale to diversify their locations and adapt to regions with fewer restrictions or more resilient infrastructure, small firms are more likely to be concentrated in areas with higher exposure to stringent climate policies. This lack of geographical diversification leaves them more vulnerable to regulatory changes and the potential economic consequences of climate-related risks, such as higher energy costs, stricter environmental regulations, or physical impacts from climate change.

Consequently, investors demand a higher premium from small firms to offset the risks of operating in more climate-sensitive regions, where the potential for policy changes and environmental disruptions may pose a significant financial burden. In contrast, larger firms, with greater resources to adapt and diversify, face relatively lower premiums, as their operations are less constrained by the climate-related risks that directly affect smaller, less flexible firms. This disparity highlights the disproportionate impact of climate risk on small firms, particularly those unable to easily relocate or adjust to the evolving regulatory landscape.

Additionally, smaller firms may be more sensitive to factors such as market risk (MKT), economic policy uncertainty (EPU_{US}) at the U.S. level, and other observed factors. In contrast, larger firms tend to exhibit risk premia that are either smaller or closer to zero for many of the Fama-French risk factors. For example, in the FF3 model, the market risk premium for small firms is -0.3094, whereas for larger firms, it is significantly higher at 1.9448. Moreover, the risk premia for SMB and HML are also more moderate for larger firms compared to those observed for small firms, further highlighting the differential sensitivity to these factors based on firm size.

Additionally, the risk premium associated with the PCI_{US} factor for small firms is estimated at 1.4894 (standard error: 0.0956), which is substantially higher than that for large firms (0.7807, standard error: 0.1009) according to the Standard Fama-MacBeth

Model results. This significant difference suggests that the PCI_{US} factor explains more variation in returns for small firms than for large firms. These findings are consistent with the finance literature, which attributes higher risk premia for small firms to their greater exposure to macroeconomic risks and limited diversification compared to larger firms.

Using the methodology proposed by Giglio and Xiu (2021), the estimated risk premium for small firms is 0.3916 (standard error: 0.3133), while for large firms, it is 0.3792 (standard error: 0.2436). Although the magnitudes are comparable, the statistical significance of these estimates is limited due to high standard errors. The Three-Pass Regression Filter methodology thus shows smaller differences in risk premia between small and large firms. However, the lack of statistical significance in both cases highlights the limited explanatory power of the PCI_{US} factor in this framework. Interestingly, the R_g^2 values indicate that the PCI_{US} factor accounts for slightly more variation in returns for large firms than for small firms. This diminished statistical significance could reflect the challenges of capturing macroeconomic risk premia using latent factors for size-differentiated portfolios. Similar findings in the literature suggest that principal component or latent factor models are more effective in capturing broad market or economic risks rather than firm-specific variations tied to size.

Focusing on the responsiveness of portfolios to state-level economic risk factors, the analysis reveals interesting dynamics. For instance, under the $ECON_{States}$ factor, small firms exhibit a risk premium of 0.5446, whereas larger firms display a higher risk premium of 1.0286. This indicates that larger firms require a greater premium to compensate for exposure to state-level economic conditions and policy uncertainties. The elevated risk premium for larger firms suggests they may be more sensitive to variations in economic performance.

This outcome could be attributed to the fact that larger firms typically operate across multiple states and regions, making them more exposed to the diverse and often conflicting economic and policy landscapes of different states. Their broader footprint means that adverse economic conditions or policy shifts in one state can have cascading effects across their operations, necessitating a higher premium to offset this increased vulnerability. Additionally, larger firms may face greater scrutiny and regulatory burdens at the state level, further amplifying their exposure to localized risks.

In contrast, smaller firms often operate within more localized or niche markets, which may insulate them from broader state-level economic fluctuations. Their narrower focus can mean they are less affected by the economic heterogeneity and policy differences across states, leading to a comparatively lower risk premium for state-level factors. This localized focus could also make small firms more agile and adaptable to specific regional conditions, reducing their perceived vulnerability to state-level economic and policy uncertainties.

These findings align with the existing literature, which highlights the localized nature of smaller firms. Small firms typically have a more concentrated geographic presence, often operating within specific states or regions, and may face greater operational and financial constraints when adapting to changes in state-level economic conditions or policy shifts. Furthermore, smaller firms may lack the resources and operational flexibility to quickly reallocate resources or adjust strategies across multiple states, making them more exposed to state-specific risks such as tax changes, regulatory adjustments, or regional economic downturns. In contrast, larger firms, often operating on a national or international scale, can diversify their operations and mitigate the adverse effects of localized risks, thereby reducing their sensitivity to state-level factors. This heightened responsiveness of small firms to state-level risk factors underscores the importance of considering firm size when assessing the broader implications of regional economic and policy fluctuations on financial performance.

In the case of EPU_{States}, smaller firms demonstrate a notably more negative risk premia (-1.0040), compared to the relatively modest negative risk premia of larger firms (-0.2782) under the Fama-MacBeth Model. This disparity highlights the heightened sensitivity of smaller firms to state-level economic policy uncertainty. The pronounced negative risk premia for smaller firms suggest that these firms are disproportionately impacted by fluctuations in state-level policy environments, likely due to their limited geographic diversification and resource constraints, which make them more vulnerable to localized economic and regulatory shifts.

Additionally, small firms exhibit a pronounced sensitivity to climate risk factors, as highlighted by the risk premium of 7.2464 for temperature anomalies at the state level in the small firms' portfolio. This significantly higher value, compared to the risk premium of 3.0963 for larger firms under the same model, underscores the heightened vulnerability of smaller firms to climate-related risks. When analysed using the Giglio and Xiu (2021) methodology, the disparity remains evident, with larger firms exhibiting a far smaller response to temperature anomalies, reflected in a risk premium of just 0.1868 under the Three-Pass Regression Filter approach.

The heightened sensitivity of small firms to state-level temperature anomalies can be attributed to their limited ability to adapt to climate-related challenges. Smaller firms often lack the financial resources, operational flexibility, and scale to implement mitigation strategies, such as relocating operations, retrofitting facilities to withstand extreme weather, or investing in energy-efficient technologies. Additionally, their reliance on localized supply chains and markets amplifies their exposure to adverse climate events, as disruptions in a specific region can have a disproportionate impact on their operations and profitability.

Conversely, larger firms are better equipped to manage and mitigate climate risks. Their broader geographic footprint allows them to diversify operations across regions, reducing their reliance on any single location that might be adversely affected by temperature anomalies. Moreover, larger firms often have greater access to capital and expertise to implement climate resilience measures, such as renewable energy adoption, infrastructure investments, and advanced risk management practices. These advantages enable them to absorb climate-related shocks more effectively, resulting in a smaller risk premium for temperature anomalies.

These findings highlight the critical role of firm size in determining vulnerability to climate risk at the state level. Policymakers and stakeholders should consider these disparities when designing climate policies and support mechanisms. For instance, targeted subsidies or incentives for small firms to invest in climate resilience measures could help mitigate their disproportionate exposure to temperature anomalies. Similarly, improving access to financing for smaller firms to address climate-related challenges could play a key role in reducing their vulnerability and ensuring a more equitable adaptation to climate risks.

In conclusion, our analysis demonstrates that smaller firms are generally more susceptible to state-level factors and climate risks, such as temperature anomalies and climate policy uncertainty, compared to their larger counterparts. This heightened sensitivity is reflected in the significantly higher risk premia associated with these factors in the portfolios of smaller firms. By contrast, larger firms exhibit a more muted response to state-level factors, such as economic policy uncertainty (EPU_{States}) and economic conditions ($ECON_{States}$), indicating their relative resilience to localized economic and policy changes. Additionally, smaller firms display larger and more volatile market risk premia, as evidenced by factors such as SMB and HML. This suggests that their higher exposure to market fluctuations may stem from constraints in financial resources, limited diversification opportunities, and a greater reliance on local or regional markets. These characteristics make smaller firms more vulnerable to systemic shocks and economic disruptions.

2.7 Conclusion

In this research, we examined risk premia in U.S. firms using the three-pass methodology proposed by Giglio and Xiu (2021), with a specific focus on climate-related transition and physical risks. Our primary objective was to evaluate how effectively U.S. asset markets price climate risk and to assess whether firms' proactive responses to climate-related challenges are reflected in market valuations. A central contribution of this study is the incorporation of a U.S. state-level climate change indicator into the model, acknowledging the heterogeneous capacity of states to respond to a relatively fragmented federal climate policy framework. This state-level dimension motivates a more nuanced approach to risk measurement and allows us to link climate risk pricing to geographical and institutional differences within the U.S.

Our empirical analysis yields clear implications for portfolio performance and investment decisions. Across specifications, the statistical significance of intercepts and risk premia supports the robustness of our estimates, while strong fit (e.g., R_g^2) and stable intercepts as the number of principal components varies indicate that the pricing relations are not driven by model instability or over-fitting. The fact that key patterns persist across alternative factor structures further strengthens confidence in the identification and reliability of our results.

Overall, our findings contribute to empirical asset pricing by implementing the Giglio and Xiu (2021) framework with a richer factor structure and an explicit state-level climate dimension, providing a more complete account of how climate-related risks are reflected in U.S. equity returns. This evidence offers practical guidance for investors and policymakers seeking to incorporate climate risk into portfolio design and to strengthen risk management amid rising climate and policy uncertainty.

Our analysis using the three-pass methodology proposed by Giglio and Xiu (2021) with varying numbers of principal components shows that different specifications and risk factors have distinct yet coherent impacts on test portfolios, in line with established principles in empirical asset pricing. The stability and consistency of the intercepts across models and principal component choices provide a reliable benchmark for expected returns. At the same time, the variation in estimated risk premia underscores the heterogeneous influence of key sources of uncertainty. In particular, the climate policy uncertainty factor (CPU_{US}) captures market-wide perceptions of climate policy risk, which translate into systematic differences in portfolio returns. Investors require higher premium in order to bear this risk (Bua et al. (2024)). The economic policy uncertainty factor (EPU_{US}) reflects how firms with different environmental, social, and governance

(ESG) profiles respond to policy unpredictability, leading to differentiated pricing across portfolios. Finally, the economic conditions indicator ($ECON_{US}$) emphasizes the role of broader macroeconomic health in shaping firm profitability and, consequently, return dynamics.

We also document novel evidence on the asset-pricing relevance of the Partisan Conflicts Index (PCI_{US}), showing that political polarisation and policy gridlock are associated with meaningful variation in portfolio returns. The PCI_{US} factor captures dimensions of political uncertainty that go beyond traditional economic indicators, reinforcing its importance in an environment of policy-driven market volatility. Moreover, the cross-sectional analysis by firm size indicates that smaller firms command higher risk premia across most factors, including climate-related risks, suggesting greater vulnerability to climate transitions and a higher required compensation for bearing such exposures. The introduction of the Normalized Climate Transition Risk Index (NCTRI) further highlights the role of climate-related discourse in asset pricing. While the standard Fama–MacBeth (FM) procedure points to a significantly negative risk premium on NCTRI, consistent with U.S. firms viewing climate transition risk as detrimental to economic activity, the three-pass methodology attenuates this pricing signal once latent factors are included. This attenuation suggests that a substantial portion of the climate-related variation in returns is absorbed by broader latent macroeconomic or climate risk factors, underscoring the need for more refined strategies to isolate climate-specific effects in asset-pricing models.

Taken together, these results not only align with core economic theories on risk compensation and uncertainty, but also offer a practical framework for investors and policymakers seeking to design climate-aware portfolios and regulatory responses. By jointly considering climate, policy, and macroeconomic uncertainty factors, our study provides clearer guidance on how to evaluate, price, and manage climate-related risks in U.S. equity markets.

Additionally, the Giglio and Xiu (2021) methodology offers valuable insights into the pricing of risk at the state level, demonstrating that incorporating additional principal components consistently enhances model fit and explanatory power. This underscores the importance of capturing unobserved factors in asset pricing. The distinct risk-return profiles observed for state level temperature anomalies ($Tanomalies$), economic policy uncertainty (EPU_{States}), and economic conditions indicator ($ECON_{States}$) provide crucial information for both policymakers and investors regarding regional economic dynamics.

Our findings align with existing literature that emphasizes the significant impact of environmental factors on economic outcomes (Ardia et al. (2023), Bolton and Kacperczyk (2023), and Pástor, Stambaugh, and Taylor (2022)). The strong and significant risk premia indicate that temperature anomalies are indeed priced in the cross-section of returns, suggesting significant implications for portfolio performance, particularly in climate-sensitive sectors. The variability and positive nature of the risk premia imply that assets in lower ESG-ranked portfolios require higher compensation for bearing temperature anomaly risks. In contrast, higher ESG-ranked portfolios might exhibit lower sensitivity to these risks, reflecting better risk management practices. The mixed and sometimes insignificant risk premia for EPU_{States} suggest that while economic policy uncertainty has some effect on returns, it is not consistently priced across all portfolios. This factor has moderate implications for performance, and its impact may vary based on other market conditions. Lastly, the generally positive and somewhat significant risk premia for $ECON_{States}$ indicate that economic conditions are priced to some extent, though not as strongly as temperature anomalies. This factor has moderate implications, especially for regionally focused investments.

From a policy perspective, our findings advocate for the integration of comprehensive state-level climate risk assessments in investment decisions. Policymakers and investors should consider these insights to tailor their strategies, enhancing resilience and optimizing returns in the face of climate-related uncertainties. Additionally, the evident pricing of climate risks and the significant role of state-level economic conditions in shaping market valuations underscore the need for policies that support transparent and consistent climate-related disclosures. Such measures would improve the accuracy of risk assessments and foster more informed investment decisions.

One of the main challenges encountered in this research was the limited availability of detailed state-level climate risk measures, particularly for transition risks arising from differences in climate policy across U.S. states. The analysis highlighted substantial heterogeneity in climate-policy adoption and implementation across states, which reinforces the need for more granular and systematically constructed measures of local climate risk. Future research could address this limitation by developing a refined state-level measure of climate transition risk, for example through text-based methods applied to legislative records from the National Conference of State Legislatures (State Legislatures n.d.) and coverage from state-level newspapers. A richer measure of this kind would improve the precision with which researchers capture variation in local climate-policy exposure and would allow for a more nuanced assessment of how state-specific transition risks are reflected in financial markets.

At the same time, an important avenue for future work is to strengthen the causal interpretation of these relationships. While the present chapter documents that state-level climate-related variables are meaningfully associated with the cross-section of returns, the estimated premia may still partly reflect correlated regional macroeconomic conditions, political environments, or other omitted local shocks. Future research could therefore build on this chapter by employing research designs that better isolate exogenous variation in climate risk, such as quasi-natural experiments, policy discontinuities across states, difference-in-differences approaches around major legislative changes, or instrumental-variable strategies based on plausibly exogenous climatic or institutional variation. Such approaches would help distinguish more clearly whether the pricing effects documented here arise from climate risk itself, from the economic channels through which climate risk operates, or from broader local conditions that are correlated with climate exposure.

Future research on climate risk could also investigate more explicitly the frequency dynamics of climate-related factors, such as temperature anomalies, extreme weather events, and broader environmental changes, which often exhibit pronounced seasonal and multi-year patterns. These temporal fluctuations imply that climate risks may affect portfolios differently across investment horizons, with sectors such as agriculture, energy, and insurance likely to be particularly exposed to seasonal and higher-frequency shocks.

A more explicit focus on frequency-specific climate risk factors may uncover exposures that remain hidden in standard time-aggregated asset-pricing models. Risks that appear modest at an annual level may display substantial volatility at higher frequencies, leading to mismeasured or insufficiently priced climate exposures. To disentangle these effects, future work could employ frequency-domain techniques, such as spectral or wavelet analysis, as well as time–frequency models or seasonal factor structures to decompose climate variables into distinct frequency components. This would allow researchers to assess how climate-related risks are priced across different horizons and to develop asset-pricing frameworks that better capture the time-varying nature of climate risk.

In conclusion, the results underscore the importance of incorporating state-level factors such as temperature anomalies, economic policy uncertainty, and economic conditions into investment strategies. While temperature anomalies demonstrate strong pricing and significant implications for portfolio performance, economic policy uncertainty and economic conditions exhibit more varied impacts that require careful consideration in portfolio management decisions. These findings highlight the relevance of regional perspectives in enhancing resilience and capturing value in increasingly complex financial markets.

Appendix B

Chapter 2

B.1 Mixed-Frequency Estimation Methodology

Let us assume that $\Delta = \frac{1}{m}$ be the sampling frequency of high-frequency returns. Let $a^h_{t+k\Delta}$ denote the high-frequency return from $t + (k-1)\Delta$ to $t + k\Delta$ for $a = r$, u, and v. By recycling the old notation a_t and using it as the low-frequency cumulative return for $t-1$ to t, that is, $a_t := \sum_{k=1}^{m-1} a^h_{t+k\Delta}$. According to Giglio et al. (2021), we should assume that the high-frequency test asset returns follow a linear factor model as the following:

$$r^h_{t+k\Delta} = \beta\gamma\Delta + \beta v^h_{t+k\Delta} + u^h_{t+k\Delta}, \tag{B.1}$$

for $1 \leq k \leq m$ and $1 \leq t \leq T$. Then we revise the procedure to make use of high-frequency returns.

Precisely, in the first two steps of the three-pass procedure, we conduct a PCA and cross-section regression as highlighted previously, however, now using $r^h_{t+k\Delta}$ in order to obtain $\hat{V}^h$, $\hat{\beta}^h$, and $\hat{\gamma}^h$, respectively, where the subscript h emphasizes the use of high-frequency data and the subscript l represents the use of low-frequency data. Note that in this case $\hat{V}^h$ is a $d \times (mT)$ matrix of the estimated high-frequency factors. Additionally, for the third step, we instead regress g_t onto the low-frequency cumulative returns of the high-frequency factors:

$$\hat{\eta}^\iota = \bar{G}\left(\hat{V}^\iota\right)^T \left(\hat{V}^\iota \left(\hat{V}^\iota\right)^T\right)^{-1}, \tag{B.2}$$

Where $\hat{V}^\iota = \hat{V}^h(\iota_m I_T)$. Consequently, the new risk premia estimator is given by:

$$\hat{\gamma}^m_g = m \times \hat{\eta}^\iota \hat{\gamma}^h. \tag{B.3}$$

Where the multiplier m ensures that the risk premia estimates are in the same unit as those based on low-frequency data (e.g., monthly frequency). According to Giglio and Xiu (2021), this estimator is asymptotically equivalent to the benchmark estimator in the previous session ($\hat{\gamma}_g$). Note that in this case the sample size is replaced by mT and the variance Σ^v is replaced by $\Sigma^v\Delta$. Supposing that all the assumptions highlighted by Giglio and Xiu (2021) hold for the lower frequency cumulative returns, v_t and u_t. Additionally, suppose that $\hat{p} \xrightarrow{p} p$; then as $n, T \to \infty$, with probability approaching 1, there exist some invertible matrix (H^h), such that:

$$\hat{\gamma}^h - H^h\gamma\Delta = m^{-1}H^h\bar{v} + O_P(n^{-1} + T^{-1}), \tag{B.4}$$

$$\hat{\eta}^\iota - \eta\left(H^h\right)^{-1} = \bar{Z}\bar{V}^T\left(\bar{V}\bar{V}^T\right)^{-1}\left(H^h\right)^{-1} + O_P(n^{-1} + T^{-1}). \tag{B.5}$$

Moreover, as a final result[1], we obtain the following estimator:

$$\hat{\gamma}_g^m = \hat{\gamma}_g + O_P(n^{-1} + T^{-1}). \tag{B.6}$$

[1]Recall that the sample average return, $\bar{v}^h = \frac{1}{mT}\sum_{t=1}^{T}\sum_{k=1}^{m} v_{t-1+k}^h$, represents the leading term of $\hat{\gamma}^h - H^h\gamma\Delta$. Additionally, the sample average remains exactly the same regardless of the sampling frequency of the observed returns ($\bar{v}^h = m^{-1}\bar{v}$).

B.2 Tables and Figures

Table B.1: **Summary Statistics for Each Portfolio**. The table displays the mean, median, standard deviation (Std), skewness, and kurtosis for each of the 20 portfolios.

Portfolio	Mean	Median	Std	Skewness	Kurtosis
1	−0.000 58	0.002 77	0.009 14	−3.007 06	12.095 11
2	−0.002 71	−0.000 74	0.006 01	−2.274 79	7.748 54
3	−0.000 06	0.003 20	0.008 05	−1.891 54	5.423 29
4	−0.005 51	−0.005 76	0.004 43	−1.181 58	5.252 30
5	−0.002 00	−0.000 59	0.006 87	−1.827 63	6.225 40
6	0.003 20	0.004 73	0.004 53	−2.636 79	9.752 05
7	0.003 68	0.004 62	0.003 11	−2.862 80	12.163 27
8	0.003 24	0.004 16	0.003 55	−2.674 88	10.341 06
9	0.002 91	0.003 82	0.002 97	−1.786 96	7.035 19
10	0.003 41	0.003 72	0.002 79	−1.445 25	7.172 14
11	0.003 16	0.002 56	0.003 15	0.724 60	3.477 99
12	0.005 33	0.004 78	0.002 91	0.559 89	2.686 34
13	0.004 93	0.004 22	0.002 84	1.632 49	6.370 19
14	0.004 88	0.004 74	0.002 07	0.011 87	2.714 03
15	0.004 47	0.004 62	0.002 41	−0.179 81	1.880 71
16	0.004 11	0.004 16	0.001 88	0.019 36	2.879 62
17	0.004 59	0.004 62	0.001 83	−0.207 74	3.288 10
18	0.003 89	0.003 71	0.002 00	−0.281 05	2.692 74
19	0.005 16	0.005 30	0.002 14	−0.049 98	2.158 57
20	0.006 24	0.006 14	0.001 49	0.010 44	2.200 12

Table B.2: **Data Description and Respective Codes.**

Name	**Frequency**	**Period**	**Code**
Adjusted Close Price	Daily	2000/03/01–2023/03/01	P
Cumulative Returns	Monthly	2000/03–2023/03	R
Total Market Portfolio Return (excess of risk-free rate)	Monthly	2000/03–2023/03	MKT
Size Premium (Small minus Big)	Monthly	2000/03–2023/03	SMB
Value Premium (High minus Low)	Monthly	2000/03–2023/03	HML
Operating Profitability (Robust minus Weak)	Monthly	2000/03–2023/03	RMW
Investment (Conservative minus Aggressive)	Monthly	2000/03–2023/03	CMA
U.S. States Economic Index Indicator	Monthly	2000/03–2023/03	ECON_States
U.S. Wide Economic Index Indicator	Monthly	2000/03–2023/03	ECON_US
Climate Policy Uncertainty Index Indicator (U.S. wide)	Monthly	2000/03–2023/03	CPU_US
Climate Policy Index Indicator (U.S. state level)	Monthly	2000/03–2020/12	CPI_States
Economic Policy Uncertainty Indicator (U.S. state level)	Monthly	2000/03–2023/03	EPU_States
Economic Policy Uncertainty Indicator (U.S. wide)	Monthly	2000/03–2023/03	EPU_US
Temperature Anomaly (U.S. state level)	Monthly	2000/03–2023/03	TAnomalies
Natural Disasters (U.S. state level)	Monthly	2000/03–2023/03	Natural_US
Partisan Conflict Index (U.S. wide)	Monthly	2000/03–2023/03	PCI_US
Normalized Climate Transition Risk Index	Monthly	2000/03–2023/03	NCTRI

Table B.3: **Risk Premia for Observed and Unobserved Factors.**

Factors	Intercept	Risk Premia	Zero-Beta Var.	Risk Premia Var.
CPU ($\hat{p} = 10$)	0.0045	0.1063***	0.0000	0.0200
FF3 MKT ($\hat{p} = 10$)	0.0045	-0.0099	0.0000	0.1426
FF3 SMB ($\hat{p} = 10$)	0.0045	0.1761	0.0000	0.1673
FF3 HML ($\hat{p} = 10$)	0.0045	0.2774	0.0000	0.2139
EPU_US ($\hat{p} = 10$)	0.0045	0.0723	0.0000	0.4404
ECON_US ($\hat{p} = 10$)	0.0045	-0.0574	0.0000	0.3185
PCI_US ($\hat{p} = 10$)	0.0045	-0.3114	0.0000	0.3664
FF5 MKT ($\hat{p} = 10$)	0.0045	-0.0099	0.0000	0.1426
FF5 SMB ($\hat{p} = 10$)	0.0045	0.1744	0.0000	0.1687
FF5 HML ($\hat{p} = 10$)	0.0045	0.2774	0.0000	0.2138
FF5 RMW ($\hat{p} = 10$)	0.0045	-0.1612	0.0000	0.2005
FF5 CMA ($\hat{p} = 10$)	0.0045	0.3254	0.0000	0.2142
Tanomalies ($\hat{p} = 10$)	0.0045	0.1422***	0.0000	0.1188
EPU_States ($\hat{p} = 10$)	0.0045	0.2241*	0.0000	0.1065
ECON_States ($\hat{p} = 10$)	0.0045	0.1700***	0.0000	0.1140

Notes: This table presents the intercept, risk premia (λ), zero-beta variance, and the variance of risk premia for both observed and unobserved factors, following Giglio and Xiu (2021). The factors CPU_{US}, EPU_{US}, $ECON_{US}$, $Tanomalies$, EPU_{States}, and $ECON_{States}$ are standardized. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table B.4: **Comparison of Standard Fama-MacBeth (FM) Model Estimates for U.S.-Wide Risk Factors and Giglio and Xiu (2021) Methodology Estimates.** This table presents the estimated intercepts and risk premia, along with their standard errors, for the CPU_{US}, EPU_{US}, $ECON_{US}$, and PCI_{US} factors. The results are derived from the Fama-MacBeth two-pass regression method. The results are shown for the four models, along with the goodness-of-fit measure R_g^2 for each factor. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model	Standard FM			Giglio and Xiu (10 PCs)			R_g^2
	Intercept	Risk Premia	Std. Error	Intercept	Risk Premia	Std. Error	
CPU_{US}	0.0037	0.9555***	0.0856	0.0045	0.1063***	0.0200	0.5941
EPU_{US}	0.0035	1.6015***	0.1395	0.0045	0.0723	0.2917	0.4404
$ECON_{US}$	0.0040	2.6936***	0.2288	0.0045	-0.0574	0.3477	0.3185
PCI_{US}	0.0032	1.8075***	0.1659	0.0045	-0.3114	0.3664	0.5283

Table B.5: **Comparison of Standard Fama-MacBeth (FM) Model and Giglio and Xiu (2021) Methodology for Fama-French Risk Factors**. This table compares the estimated intercepts, risk premia, and standard errors from the Fama-MacBeth (FM) model and the Three-Pass Regression Filter (3PRF) methodology by Giglio and Xiu (2021). Results are shown for both the Fama-French three-factor (FF3) and five-factor (FF5) models. The risk factors include MKT (market), SMB (small minus big), HML (high minus low), RMW (robust minus weak), and CMA (conservative minus aggressive). Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**			R_g^2
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**	
FF3	MKT	0.0042	5.0783***	0.3428	0.0045	-0.0099	0.1426	0.0302
	SMB		0.3206	0.5436		0.1761	0.1673	0.0274
	HML		9.9083***	0.4243		0.2774	0.2139	0.0718
FF5	MKT	0.0040	4.9465***	0.3094	0.0045	-0.0099	0.1426	0.0302
	SMB		2.3935***	0.3798		0.1744	0.1687	0.0284
	HML		6.3616***	0.2597		0.2774	0.2138	0.0718
	RMW		-2.9438***	0.2569		-0.1612	0.2005	0.0710
	CMA		8.4491***	0.4919		0.3254	0.2142	0.0712

Table B.6: **Comparison of Standard Fama-MacBeth (FM) Model and Giglio and Xiu (2021) Methodology for U.S. State-Level Risk Factors**. This table compares the estimated intercepts, risk premia, and standard errors from the Standard Fama-MacBeth (FM) model and the Giglio and Xiu methodology (using 10 PCs) for U.S. state-level risk factors: Tanomalies, EPU_{States}, and $ECON_{States}$. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model	**Factor**	**Standard FM**			**Giglio and Xiu (10 PCs)**			R_g^2
		Intercept	**Risk Premia**	**Std. Error**	**Intercept**	**Risk Premia**	**Std. Error**	
State-Level	Tanomalies	0.0039	4.2121***	0.3479	0.0045	0.1422***	0.1188	0.4640
	EPU_States	0.0032	1.5217***	0.1469	0.0045	0.2241	0.3018	0.4774
	ECON_States	0.0041	2.8582***	0.2292	0.0045	0.1700	0.3404	0.3251

Table B.7: **Three-Pass Methodology and Standard Fama-MacBeth (FM) Results for 38 States**. This table presents the empirical results using the Three-Pass Regression Filter (3PRF) and the Standard FM methodology for 38 U.S. states, using four and 10 principal components (PCs) as suggested factors. The table shows the intercepts and risk premia for both methodologies, along with the R_g^2 for 10 PCs.

State	Intercept (FM)	FM Risk Premia	Intercept (Three-Pass)	Risk Premia (4 PCs)	Risk Premia (10 PCs)	R²g (10 PCs)
Alabama	0.0032 (0.0001)	3.5432 (0.3912)	0.0045 (0.0006)	-0.0348 (0.0990)	-0.0687 (0.1759)	0.056144
Arizona	0.0026 (0.0001)	1.2232 (0.3451)	0.0045 (0.0006)	-0.0838 (0.1169)	-0.0352 (0.2181)	0.088512
Arkansas	0.0033 (0.0001)	6.5426 (0.6665)	0.0045 (0.0006)	0.0213 (0.0887)	-0.0461 (0.1929)	0.025927
California	0.0033 (0.0001)	3.5048 (0.3154)	0.0045 (0.0006)	-0.0082 (0.1325)	0.1335 (0.2252)	0.12245
Colorado	0.0026 (0.0001)	3.0184 (0.4854)	0.0045 (0.0006)	-0.0674 (0.1018)	0.0057 (0.2009)	0.058119
Connecticut	0.0039 (0.0000)	3.4534 (0.2780)	0.0045 (0.0006)	0.1755 (0.0862)	0.1376 (0.1951)	0.068999
Delaware	0.0036 (0.0001)	3.9384 (0.3548)	0.0045 (0.0006)	0.0673 (0.0836)	0.0149 (0.1811)	0.05785
Florida	0.0036 (0.0001)	2.4611 (0.2313)	0.0045 (0.0006)	0.0354 (0.1081)	-0.0276 (0.1753)	0.11631
Georgia	0.0029 (0.0001)	2.9765 (0.4117)	0.0045 (0.0006)	-0.0692 (0.1052)	-0.1988 (0.1904)	0.069509
Illinois	0.0034 (0.0001)	7.9214 (0.7056)	0.0045 (0.0006)	0.0136 (0.0854)	0.0496 (0.1729)	0.020549
Indiana	0.0033 (0.0001)	6.3605 (0.6406)	0.0045 (0.0006)	0.0007 (0.0836)	-0.0369 (0.1815)	0.022326
Kansas	0.0035 (0.0001)	13.2899 (0.9664)	0.0045 (0.0006)	0.0262 (0.0826)	0.1740 (0.1771)	0.013465
Maryland	0.0036 (0.0001)	3.9366 (0.3540)	0.0045 (0.0006)	0.0641 (0.0874)	0.0396 (0.1831)	0.054086
Massachusetts	0.0040 (0.0000)	3.1338 (0.2503)	0.0045 (0.0006)	0.1951 (0.0844)	0.1709 (0.1908)	0.074477
Michigan	0.0037 (0.0001)	5.9018 (0.4925)	0.0045 (0.0006)	0.0353 (0.0900)	0.1202 (0.1797)	0.036951
Minnesota	0.0030 (0.0001)	10.4652 (0.6934)	0.0045 (0.0006)	0.0055 (0.0794)	0.1800 (0.1989)	0.035742
Missouri	0.0031 (0.0001)	8.4247 (0.7034)	0.0045 (0.0006)	0.0342 (0.0917)	0.0993 (0.1815)	0.026001
Nebraska	0.0035 (0.0001)	10.5453 (0.7400)	0.0045 (0.0006)	0.0174 (0.0850)	0.2506 (0.1837)	0.032221
Nevada	0.0028 (0.0001)	5.0350 (0.4361)	0.0045 (0.0006)	-0.0394 (0.1286)	0.1515 (0.2179)	0.10041
New Hampshire	0.0041 (0.0000)	3.5899 (0.2800)	0.0045 (0.0006)	0.1997 (0.0860)	0.1583 (0.1996)	0.064409
New Jersey	0.0038 (0.0000)	3.6784 (0.3068)	0.0045 (0.0006)	0.1275 (0.0867)	0.1188 (0.1839)	0.060971
New Mexico	0.0027 (0.0001)	3.3317 (0.4822)	0.0045 (0.0006)	-0.0777 (0.1133)	-0.0741 (0.2065)	0.057634
New York	0.0039 (0.0000)	5.4023 (0.4395)	0.0045 (0.0006)	0.0945 (0.0830)	0.0396 (0.1895)	0.03351
North Carolina	0.0032 (0.0001)	3.1731 (0.3488)	0.0045 (0.0006)	-0.0377 (0.0952)	-0.0066 (0.1801)	0.059031
Ohio	0.0034 (0.0001)	4.8174 (0.4737)	0.0045 (0.0006)	-0.0018 (0.0861)	-0.0136 (0.1760)	0.028758
Oklahoma	0.0035 (0.0001)	7.2914 (0.6098)	0.0045 (0.0006)	0.0597 (0.0966)	0.0739 (0.1962)	0.030511
Oregon	0.0029 (0.0001)	5.2903 (0.4210)	0.0045 (0.0006)	-0.0476 (0.1417)	0.3072 (0.2464)	0.12052
Pennsylvania	0.0036 (0.0001)	4.9061 (0.4322)	0.0045 (0.0006)	0.0503 (0.0835)	0.0380 (0.1795)	0.033448
Rhode Island	0.0039 (0.0000)	3.0597 (0.2462)	0.0045 (0.0006)	0.1900 (0.0850)	0.1747 (0.1883)	0.079058
South Carolina	0.0035 (0.0001)	3.7742 (0.3788)	0.0045 (0.0006)	0.0177 (0.0862)	-0.0364 (0.1865)	0.05614
South Dakota	0.0032 (0.0001)	9.9079 (0.6530)	0.0045 (0.0006)	0.0004 (0.0871)	0.3127 (0.2041)	0.047601
Tennessee	0.0035 (0.0001)	5.0632 (0.4860)	0.0045 (0.0006)	0.0402 (0.0869)	-0.0060 (0.1871)	0.032152
Texas	0.0030 (0.0001)	5.5146 (0.6271)	0.0045 (0.0006)	-0.0259 (0.0822)	0.0108 (0.1117)	0.023316
Utah	0.0027 (0.0001)	4.7893 (0.4728)	0.0045 (0.0006)	-0.0532 (0.1128)	0.0616 (0.2148)	0.083185
Vermont	0.0041 (0.0000)	4.0776 (0.3111)	0.0045 (0.0006)	0.2008 (0.0884)	0.1361 (0.1986)	0.057901
Virginia	0.0032 (0.0001)	4.1208 (0.4397)	0.0045 (0.0006)	-0.0174 (0.0943)	-0.0427 (0.1776)	0.036368
Washington	0.0030 (0.0001)	5.3935 (0.4186)	0.0045 (0.0006)	-0.0324 (0.1389)	0.3612 (0.2520)	0.12505
Wisconsin	0.0032 (0.0001)	8.6153 (0.6810)	0.0045 (0.0006)	-0.0005 (0.0840)	0.1339 (0.1887)	0.03615

Table B.8: **Three-Pass Procedure Methodology Results for Selected States**. This table presents the empirical results from the Standard Fama-MacBeth (FM) methodology and the Three-Pass Regression Filter (3PRF) methodology for selected U.S. states. The estimates include intercepts and risk premia, with standard errors in parentheses. The results are shown for models using 4 and 10 principal components (PCs), along with the R_g^2 values for each factor. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model	Alabama	Arizona	Arkansas	California	Illinois	Wisconsin
Standard FM (estimate - standard error)						
Intercept	0.0032	0.0026	0.0033	0.0033	0.0034	0.0032
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
FM risk premia	3.5432***	1.2232***	6.5426***	3.5048***	7.9214***	8.6153***
	(0.3912)	(0.3451)	(0.6665)	(0.3154)	(0.7056)	(0.6810)
Three-Pass (estimate - standard error)						
Using 4 PCs						
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Risk premia	-0.0348	-0.0838	0.0213	-0.0082	0.0136	-0.0005
	(0.0990)	(0.1169)	(0.0887)	(0.1325)	(0.0854)	(0.0840)
R_g^2 for each factor	0.0353	0.0249	0.0129	0.0706	0.0079	0.0048
Using 10 PCs						
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk premia	-0.0687	-0.0352	-0.0461	0.1335	0.0496	0.1339
	(0.1759)	(0.2181)	(0.1929)	(0.2252)	(0.1729)	(0.1887)
R_g^2 for each factor	0.0561	0.0885	0.0259	0.1225	0.0205	0.0361

Table B.9: **Climate Transition Risk Factor Analysis by State (2000–2020)**. This table presents the empirical results for the standard Fama-MacBeth (FM) methodology and the Three-Pass Regression Filter (3PRF) methodology, using 4 and 10 principal components (PCs). The intercepts, risk premia, and R_g^2 values are reported with their standard errors in parentheses. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model	Alabama	Arizona	Arkansas	California	Colorado
Standard FM (estimate - standard error)					
Intercept	0.0032	0.0026	0.0033	0.0033	0.0034
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Risk premia	1.0328***	0.8495***	0.8332***	0.8166***	0.7338***
	(0.0729)	(0.0711)	(0.0700)	(0.0752)	(0.0691)
Three-Pass (estimate - standard error)					
Using 4 PCs					
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Risk premia	0.7799	0.7743	0.8074	0.6732	0.7567
	(0.4464)	(0.4525)	(0.4262)	(0.4244)	(0.4388)
R_g^2 for each factor	0.7817	0.8467	0.8411	0.7480	0.8868
Using 10 PCs					
Intercept	0.0045	0.0045	0.0045	0.0045	0.0045
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk premia	0.8723	0.7250	0.6093	0.9173	0.8280
	(0.4322)	(0.3729)	(0.3774)	(0.4144)	(0.3682)
R_g^2 for each factor	0.9083	0.9334	0.9437	0.8938	0.9630

Table B.10: **Comparison of NCTRI Risk Premia Using Standard Fama-MacBeth (FM) and Giglio and Xiu (2021) Methodology.** This table presents the estimated intercepts, risk premia, and standard errors for the NCTRI factor under the Standard Fama-MacBeth (FM) model and the Three-Pass Regression Filter (3PRF) methodology by Giglio and Xiu (2021). The generalized R-squared (R_g^2) indicates the proportion of time-series variation in the test portfolios explained by the NCTRI risk factor. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Methodology	**Intercept**	**Risk Premia**	**Std. Error**	R_g^2
Fama-MacBeth (FM)	0.0035	-3.5745***	0.3130	–
Giglio and Xiu (2021)	0.0045	-0.1519	0.2171	0.1424

Table B.11: **Comparison of Risk Premia for Observed and Latent Factors for Portfolios of Small Firms.** *Notes: This table compares the estimated intercepts, risk premia, and standard errors obtained from the Standard Fama-MacBeth (FM) model and the Three-Pass Regression Filter methodology proposed by Giglio and Xiu. The analysis includes both observed and latent factors, with results based on 10 principal components. Additionally, the R_g^2 values for each factor are provided for the Three-Pass Regression Filter methodology. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Model	Factor	Standard FM			Giglio and Xiu (10 PCs)			R_g^2
		Intercept	Risk Premia	Std. Error	Intercept	Risk Premia	Std. Error	
CPU	-	0.0034	1.5724***	0.0965	0.0032	0.3724	0.2771	0.5604
FF3	MKT	-0.0012	-0.3094	0.3332	0.0032	0.2670	0.1596	0.0506
	SMB		2.9543***	0.3578		0.1987	0.1772	0.0285
	HML		-3.7215***	0.2467		-0.4875	0.2013	0.1178
FF5	MKT	-0.0012	-1.3807***	0.3216	0.0032	0.2670	0.1596	0.0506
	SMB		1.7671***	0.3603		0.1905	0.1730	0.0278
	HML		-2.1182***	0.2576		-0.4877	0.2013	0.1178
	RMW		-2.9884***	0.2255		-0.3842	0.2189	0.1381
	CMA		-3.1161***	0.1927		-0.6587	0.2142	0.1498
EPU_US	-	0.0010	0.7616***	0.1029	0.0032	-0.0844	0.3073	0.3313
ECON_US	-	0.0010	0.3660	0.1137	0.0032	-0.2404	0.2891	0.3293
Tanomalies	-	0.0040	7.2464***	0.2943	0.0032	0.2298	0.1797	0.0542
EPU_States	-	-0.0014	-1.0040	0.1055	0.0032	-0.0001	0.2763	0.3354
ECON_States	-	0.0010	0.5446	0.1146	0.0032	-0.2575	0.2737	0.3426
PCI_US	-	0.0010	1.4894***	0.0956	0.0032	0.3916	0.3133	0.4435

Table B.12: **Comparison of Risk Premia for Observed and Latent Factors for Portfolios of Larger Firms.** *Notes: The analysis includes both observed and latent factors, with results based on 10 principal components. Additionally, the R_g^2 values for each factor are provided for the Three-Pass Regression Filter methodology. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.*

Model	Factor	Standard FM			Giglio and Xiu (10 PCs)			R_g^2
		Intercept	Risk Premia	Std. Error	Intercept	Risk Premia	Std. Error	
CPU	-	0.0056	0.6649***	0.0890	0.0059	0.2742	0.1870	0.5470
FF3	MKT	0.0058	1.9448***	0.3693	0.0059	-0.0232	0.0893	0.0372
	SMB		-1.7213***	0.3421		-0.0609	0.1045	0.0384
	HML		0.7474***	0.2099		0.0271	0.1368	0.1059
FF5	MKT	0.0057	1.7602***	0.3617	0.0059	-0.0232	0.0893	0.0372
	SMB		-2.1089***	0.3310		-0.0662	0.1030	0.0383
	HML		0.9840***	0.2081		0.0270	0.1368	0.1058
	RMW		-0.0328	0.2416		0.0152	0.1555	0.1195
	CMA		0.4966**	0.2450		-0.0382	0.1264	0.0851
EPU_US	-	0.0055	0.4146***	0.1211	0.0059	-0.1967	0.2619	0.5096
ECON_US	-	0.0059	0.9147***	0.1118	0.0059	0.3156	0.2380	0.5474
Tanomalies	-	0.0055	3.0963***	0.3239	0.0059	0.1868	0.1148	0.0661
EPU_States	-	0.0055	0.4382***	0.1253	0.0059	-0.2782	0.2548	0.5006
ECON_States	-	0.0060	1.0286***	0.1131	0.0059	0.4215	0.2501	0.5006
PCI_US	-	0.0054	0.7807***	0.1009	0.0059	0.3792	0.2436	0.4986

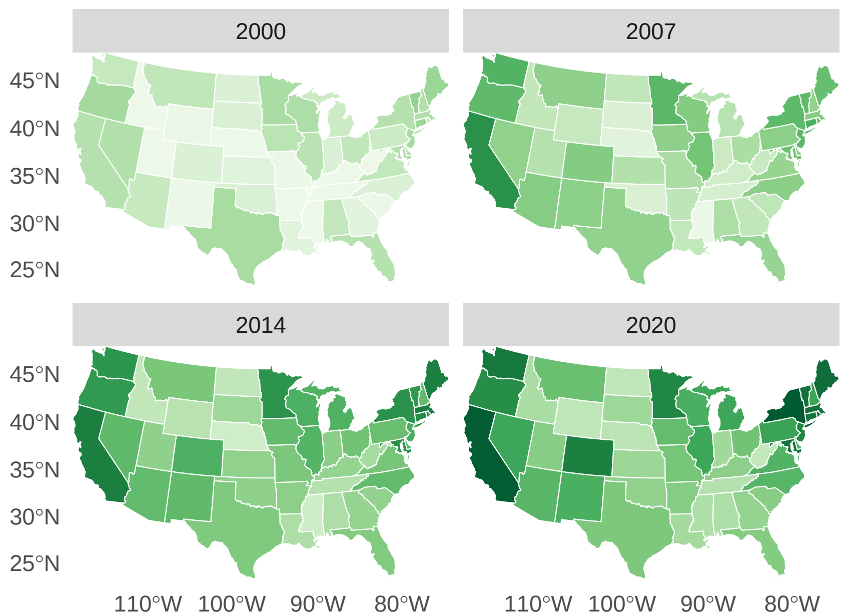


Figure B.1: **State Climate Policy, 2000–2020.** The map illustrates the number and strength of climate policies enacted by each state from 2000 to 2020. States are shaded in varying shades of green to indicate their climate policy activity, with darker greens representing states that have implemented a greater number of robust climate policies, and lighter greens representing states with fewer and less stringent policies. This visualization was created using the R package Tigris and is based on spatial data provided by the US Census Bureau. Source: Bergquist and Chris Warshaw (2023)

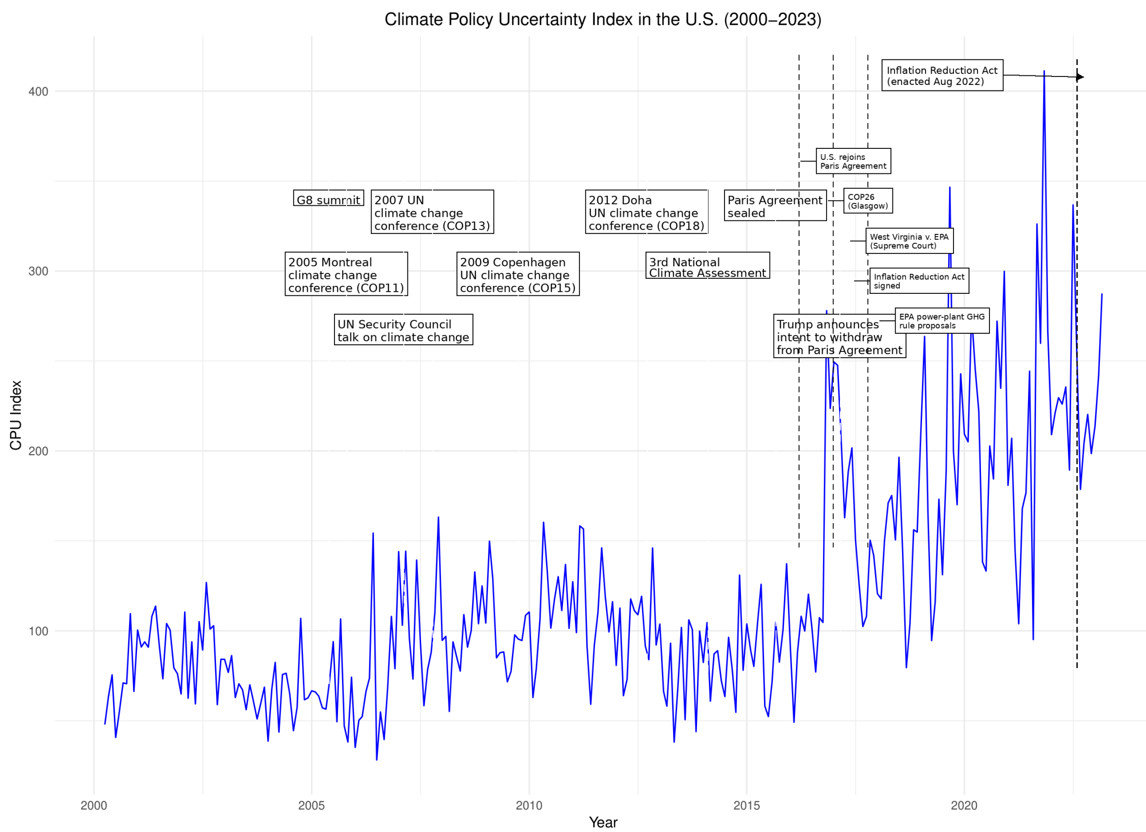


Figure B.2: **Climate Policy Uncertainty (CPU_{US}) index and U.S. (2000-2023).** Monthly U.S. Climate Policy Uncertainty index (CPU_{US}). The blue line shows the evolution of climate policy uncertainty over time; dashed vertical lines and call-outs mark major climate-policy, regulatory, legal, and international events (e.g., UN climate conferences, the Paris Agreement and related U.S. policy shifts, key EPA actions and Supreme Court rulings, and the Inflation Reduction Act).

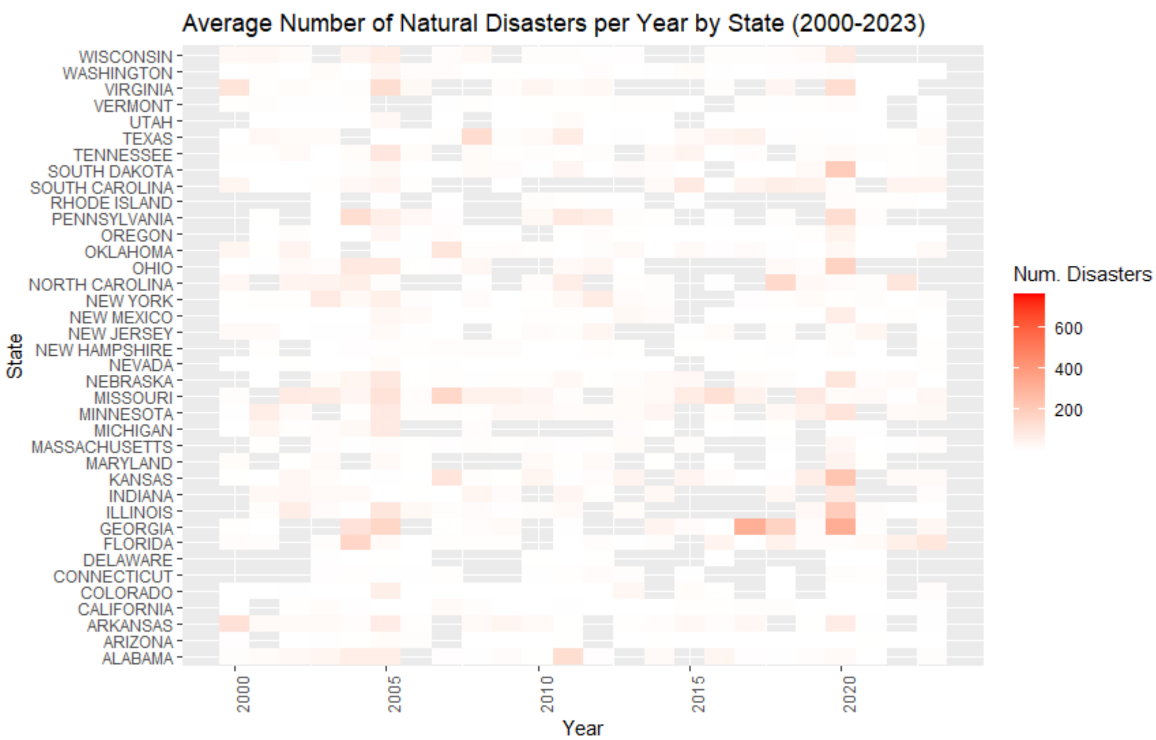


Figure B.3: **Cumulative number of natural disasters across all 38 U.S. states throughout the entire period from 2000 to 2023.** Source: National Centers for Environmental Information (NOAA/NCEI) (n.d.).

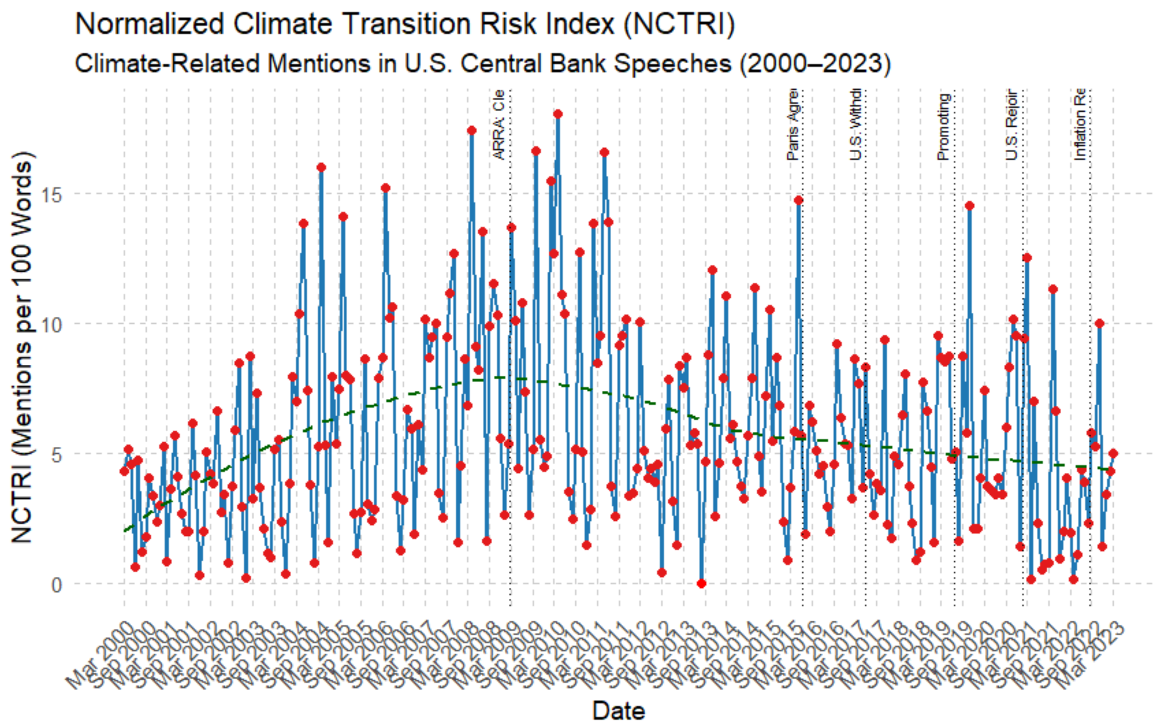


Figure B.4: **Normalized Climate Transition Risk Index (NCTRI) in the U.S.** The NCTRI captures the evolution of climate-related discourse in U.S. central bank speeches from March 2000 to March 2023, reflecting the frequency and intensity of climate-related mentions, normalized by speech length.

Chapter 3

Extracting the Informative Signal in ESG Ratings Using Frequency-Domain Methods

Abstract

Does the slow-moving component of ESG ratings predict long-term firm performance and risk pricing? The main objective of this article is to investigate the informational value of Environmental, Social, and Governance (ESG) ratings in asset pricing, addressing the growing concern about their inconsistency and noise. Rather than proposing a new ESG metric, we explore whether the slow-moving components of existing ESG scores capture persistent financial signals relevant for predicting firm performance and return variation. Drawing on the frequency-domain framework, we decompose firm-level ESG connectedness into short- and long-term components and assess their predictive power over future returns across both green and brown firms in the U.S. market. Using a dynamic factor model and spectral tools, we uncover strong evidence of horizon-dependent and sector-specific ESG effects. For green firms, predictability emerges first in the short-frequency component and strengthens with horizon; the long-frequency leg becomes clearly significant only at longer horizons. For brown firms, the signal arrives earlier and more broadly: long-frequency effects show up even at short horizons, and both bands are strongly significant from the mid-teens onward. These findings demonstrate that ESG ratings, despite their short-term noise, contain a meaningful long-term pricing signal, offering actionable guidance for investors and policymakers integrating ESG into dynamic asset-pricing frameworks.

3.1 Introduction

Sustainable investing has expanded rapidly, and ESG-integrated funds now command sizeable inflows and a central place in institutional portfolios Hartzmark and Sussman (2019). This shift has increased reliance on third-party ESG ratings as inputs to security selection and risk assessment. Yet, unlike credit ratings, ESG scores often disagree sharply across providers because of differences in coverage, indicator choices, weighting schemes, and data construction Berg, Fabisik, and Sautner (2021), Gibson Brandon, Krueger, and Schmidt (2021), and Berg, Koelbel, et al. (2022). Such divergence raises concerns about the reliability and informational content of ESG data, making it harder to interpret ESG signals in both asset pricing and corporate decision-making.

At the same time, the financial system is undergoing a broader transition toward sustainability, and ESG ratings have moved from a peripheral metric to a feature of valuation and capital allocation. Their lack of consistency therefore creates practical uncertainty for investors, regulators, and researchers. Prior work highlights a noise-to-signal problem in ESG data, showing that measurement error can mask economically meaningful information Berg, Koelbel, et al. (2022) and Chatterji et al. (2016). Against this backdrop, rather than proposing yet another score, this paper asks a more fundamental question: *Does the slow-moving component of ESG ratings contain incremental information about long-horizon firm performance and risk pricing?*

To answer this question, we introduce a novel perspective: the possibility that the true ESG signal is embedded in a slow- and high-moving component, with transitory fluctuations largely representing noise. If ESG-related financial signals emerge primarily over medium to long horizons, then short-term variations may obscure their fundamental informativeness. This motivates the application of frequency domain methods, which are particularly effective in disentangling persistent trends from transient fluctuations.

A time-varying dynamic factor framework proposed by Barigozzi, Hallin, et al. (2020) is particularly well suited to this setting for three reasons. First, simpler alternatives such as static factor models, rolling regressions, or aggregate ESG indices are less able to distinguish between common and idiosyncratic variation when ESG information is both noisy and heterogeneous across firms. Second, because the pricing relevance of ESG is likely to evolve with changes in regulation, investor preferences, and transition risk, a time-invariant specification may obscure economically meaningful shifts in the strength and transmission of ESG-related shocks. Third, the dynamic factor structure is especially valuable in a frequency-domain context, as it allows us to recover latent common components that vary over time and across horizons, rather than imposing a single homogeneous ESG effect. In this sense, the methodology is not only a statistical refinement, but a necessary tool for identifying the persistent, systematic part of ESG information that simpler approaches would likely confound with transitory noise or firm-specific movements. A further motivation for our approach comes from the dynamic factor literature on persistent common components. Barigozzi, Lippi, and Luciani (2015) show that when latent factors are non-stationary and cointegrated, dynamic factor models admit an error-correction representation that distinguishes between permanent and transitory common shocks. This is particularly relevant in our setting because ESG-related information is plausibly persistent, yet not purely trend-like: some components may reflect long-run structural adjustment, whereas others capture shorter-lived deviations. Their framework therefore provides theoretical support for modelling ESG connectedness through a dynamic factor structure capable of accommodating common stochastic trends while preserving economically meaningful short-run adjustment dynamics.

Our empirical strategy builds on the time-varying general dynamic factor framework of Barigozzi, Hallin, et al. (2021) to decompose firm-level ESG connectedness into short- and long-frequency components. We interpret ESG connectedness as a measure of systematic ESG risk,[1] namely, the common ESG-related component of return co-movement rather than firm-specific variation. This distinction is important because ESG information is unlikely to be incorporated into prices at a uniform speed across horizons: short-run fluctuations are more likely to reflect transitory news, revisions in expectations, or investor sentiment, whereas long-run components are more closely linked to persistent changes in firm fundamentals, regulatory exposure, transition risk, and the gradual reassessment of business models. The frequency decomposition therefore provides an economically meaningful way to distinguish between temporary ESG-related pricing effects and more persistent sources of risk that investors may require compensation for bearing. It also allows us to test whether slow-moving (long-run) ESG components[2]

[1]The reconceptualisation of ESG ratings as systematic information rests on the idea that ESG indicators matter for asset pricing not only because they contain firm-specific sustainability signals, but also because they transmit common information that investors process jointly across firms. When changes in ESG assessments induce co-movement in returns, they no longer operate as purely idiosyncratic characteristics, but instead reflect market-wide informational channels associated with shared regulatory exposure, transition risk, reputational repricing, and shifts in investor preferences. In this sense, the relevant pricing object is not the raw ESG score itself, but the common component extracted from the cross-section of firms, which captures the extent to which ESG-related information is systematic rather than noise. This motivates our focus on ESG connectedness as a measure of systematic ESG information.

[2]Economically, the distinction between short- and long-frequency ESG components reflects differences in the speed with which ESG-related information is incorporated into asset prices. Short-run components are more likely to capture high-frequency adjustments to news, temporary revisions in expectations,

contain greater predictive content for returns and risk premia than faster, cash-flow-oriented (short-run) components. In doing so, we provide a tool to filter ESG noise and to incorporate frequency-specific ESG risk into dynamic asset-pricing models, thereby delivering sharper tests of how ESG is priced across investment horizons. Another important methodological foundation for our analysis is the frequency-connectedness framework of Baruník and Křehlík (2018). Their approach shows that connectedness is not a single aggregate object, but depends on the frequency at which shocks are transmitted across the system. Using the spectral representation of forecast error variance decompositions, they distinguish between short-, medium-, and long-run connectedness, thereby allowing researchers to identify whether spillovers are transitory or persistent. This insight is central to our study because ESG-related information is unlikely to be incorporated into prices uniformly across horizons. By adopting a frequency-domain perspective, we can distinguish short-run ESG spillovers associated with temporary adjustment from long-run connectedness linked to more persistent risk transmission.

Three key motivations drive this research. First, widespread inconsistencies in ESG scores reduce their credibility as financial predictors. To address this, we employ ESG data from both Refinitiv and Bloomberg, constructing a cross-validated dataset to isolate reliable ESG signals. Second, inspired by long-run risk theories (Chu et al. (2020)), we build on the insight that financial information embedded in low-frequency components is more relevant for long-term pricing. We test whether the ESG–return relationship strengthens over longer forecast horizons, in line with theories suggesting that the market gradually incorporates sustainability-related information over time (e.g., Pedersen, Fitzgibbons, and Pomorski (2021); Chu et al. (2020); Berg, Fabisik, and Sautner (2021)). Third, while previous studies document the role of ESG in explaining the cross section of returns, empirical findings remain mixed. Some studies find that high ESG ratings predict higher returns, often attributed to improved risk management, stakeholder engagement, or long-term value creation (Albuquerque et al. (2020); Edmans (2011); Hoepner et al. (2024)). Others find that higher ESG ratings are associated with lower expected returns, as sustainable assets attract price premiums due to investor preferences, resulting in lower future performance (Pástor, Stambaugh, and Taylor (2021)). Our study seeks to reconcile these perspectives by incorporating both frequency decomposition and firm heterogeneity, recognising that the impacts of ESG can vary

earnings-related announcements, sentiment, or other transitory shocks that affect cash-flow expectations over relatively brief horizons. By contrast, long-run components reflect more persistent and gradual forces, such as regulatory change, climate transition exposure, evolving investor preferences, reputational capital, and adjustments in firms' underlying business models. These slower-moving components are therefore more likely to proxy for systematic ESG-related risks that matter for discount rates and expected returns over longer investment horizons.

across time horizons and between green and brown firms.

Our results reveal strong evidence that ESG connectedness, measured as an aggregate, market-wide (systematic) signal, predicts returns in a frequency- and firm-type-dependent manner, with the slow-moving (long-frequency) component playing the central role. For green firms, short-frequency predictability appears early and strengthens monotonically with the horizon, but the decisive gains arrive on the long-frequency leg: significance emerges around 13 month horizon and tightens sharply through the two-year mark, where long-run connectedness dominates the forecasting profile. This pattern is consistent with ESG information operating as slow-moving intangible capital, reputation, stakeholder trust, and strategic alignment Chu et al. (2020), whose effects are incorporated progressively into prices as transition dynamics unfold.

Brown firms display earlier and broader sensitivity to the same systematic ESG signal, especially on the long-frequency dimension. Long-run connectedness is already detectable at very short horizons (around 1 to 2 months horizon) experiences a mild lull in the mid-teens, and then becomes strongly significant at longer horizons; short-frequency effects accumulate more gradually and are uniformly significant from the mid-teens to two years. These results align with a view in which brown firms face both slow-moving transition forces (policy, technology, supply-chain realignment) and operational adjustments that take several reporting cycles to materialize, leading to earlier detection of long-run pricing and later tightening of short-run effects.

Sectoral patterns reinforce the primacy of the long-frequency channel. Among green firms, most sectors exhibit wider dispersion and higher medians in the long-frequency betas than in the short-frequency ones, indicating systematic, persistent pricing of ESG exposures beyond idiosyncratic events. For brown firms, sectoral heterogeneity is pronounced, industrials show wide spreads while communication services tilt negative on median, suggesting that long-run ESG risk is priced with different intensities across industries. Taken together, the results highlight that (i) ESG connectedness carries a slow-moving component that forecasts returns, and (ii) the strength and timing of this component are firm-type and sector dependent, justifying a frequency-domain approach to ESG in asset pricing.

These findings demonstrate that ESG ratings, despite their inconsistencies, contain meaningful pricing signals when viewed through a frequency-specific and firm-type lens. Our study complements prior work, such as Chu et al. (2020), by reinforcing the time-series informativeness of ESG ratings and extending the literature by incorporating spectral decomposition to reveal hidden dynamics in ESG-related return predictability. More importantly, our approach departs from the conventional use of raw ESG levels by focusing on ESG connectedness, that is, the extent to which ESG-related information generates common variation across firms. This has an important advantage in a setting characterised by rating disagreement: while raw ESG scores are highly sensitive to provider-specific methodologies, coverage decisions, and weighting schemes, connectedness is designed to capture the common component of ESG information that is transmitted through the cross-section. In this sense, ESG connectedness is less dependent on the absolute level assigned by any one provider and more informative about the systematic part of ESG information that is relevant for asset pricing.

A major concern in ESG research remains measurement error. Berg, Koelbel, et al. (2022) estimate the noise-to-signal ratio in ESG ratings and propose aggregating multiple providers to mitigate bias. While data constraints often limit this approach, our use of two widely adopted providers, Refinitiv and Bloomberg, helps balance signal extraction with practical feasibility. The focus on ESG connectedness provides a further safeguard against this problem. Rather than treating each observed ESG level as a precise measure of firm sustainability, the connectedness framework emphasises the co-movement and spillover structure embedded in ESG information. To the extent that measurement error is partly idiosyncratic to firms or providers, it is less likely to survive in the common dynamic component than in raw scores themselves. This makes connectedness especially valuable when disagreement across ratings clouds inference, because it shifts attention from noisy levels to the persistent and shared informational content that is more likely to be priced. We focus on the U.S. equity market, particularly the energy and industrial sectors, where ESG dynamics are especially pronounced.

The broader theoretical context supports our approach. Models by Pástor, Stambaugh, and Taylor (2021) show that green firms may enjoy valuation uplifts due to investor preferences and anticipated regulation, while brown firms face persistent valuation discounts. Yet, these mechanisms depend on how markets process information over time. Recent work by Gospodinov, Gaffney, and Ng (2025) argues for separating low- and high-frequency signals in environmental data, such as temperature. We extend this logic to ESG: just as climate data contain persistent and transitory components, ESG scores can reflect both structural firm alignment and short-term noise. Recognising this duality is essential for understanding ESG's role in asset pricing. In this framework, ESG connectedness is particularly useful because it links ESG information to the way markets actually absorb and price common shocks. Whereas raw ESG levels primarily describe firm-specific standing at a point in time, connectedness captures how ESG-related information propagates across firms and sectors, thereby providing a closer proxy for systematic risk transmission. This is especially relevant in asset pricing, where common variation, rather than isolated firm characteristics, is the channel through which risks are typically priced.

In summary, this study addresses the core debate in ESG investing: whether ratings reflect economically meaningful signals or merely noisy labels. By applying frequency-domain tools to ESG connectedness and linking them to future returns, we show that ESG spillovers are priced heterogeneously across time and sectors. Our findings have practical implications: investors can benefit from emphasising long-term ESG components, while policymakers should recognise that ESG integration unfolds dynamically and is not uniformly priced across firms.

The remainder of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 details the methodology. Section 4 presents the data. Section 5 discusses the empirical findings and economic interpretations. Section 6 provides robustness checks with sectoral level decompositions and the final section concludes.

3.2 Literature Review

Sustainable investing has experienced rapid growth, with mutual funds that incorporate ESG ratings attracting substantial inflows (Hartzmark and Sussman (2019)). As a result, investors increasingly rely on ESG ratings as third-party assessments of corporate sustainability performance. This growing reliance has sparked significant interest among academics, practitioners, and policymakers, particularly in understanding the relationship between ESG performance and financial variables, such as stock returns. However, measuring ESG performance remains inherently challenging, as ESG rating agencies[3] often produce divergent assessments for the same firms. This lack of consistency raises important questions about the informational content of ESG ratings and their broader implications for asset prices and corporate decision-making. For instance, as noted in the Wall Street Journal, "Environmental, social and governance criteria are hard to define. When we measure how different ESG providers rate companies in the S&P 500, there's often little overlap. By contrast, when ratings agencies score those same companies for their creditworthiness, they are much more often in agreement" (Kent and Sindreu (2018)). Against this backdrop, our research aims to contribute to the literature by examining whether ESG ratings contain an informative signal beyond the noise.

Our paper contributes to several strands of literature, particularly the growing body of research emphasising the noisiness of ESG ratings as measures of ESG performance. A critical issue in ESG research is the divergence of ESG ratings, which adds significant noise to ESG measures. Berg, Koelbel, et al. (2022) analyse ESG ratings from six leading ESG rating agencies, demonstrating that ESG scores vary widely across providers. This inconsistency makes it challenging for investors, firms and policymakers to interpret ESG ratings reliably. Chatterji et al. (2016) identifies two key reasons for this divergence: theorization, differences in what ESG raters choose to measure; commensurability, variations in how these metrics are measured and scored. Tang (2022) shows that institutional ownership ties can introduce bias, with MSCI assigning higher ESG scores

[3]In response to growing investor and regulatory demand for sustainability-related information, ESG rating agencies have become central information intermediaries in global capital markets. These agencies, such as MSCI (2018), Thomson Reuters (2017), and Sustainalytics (2018), collect, evaluate, and synthesise vast quantities of environmental, social, and governance data to produce firm-level ESG ratings. These ratings are designed to assess how effectively a company manages ESG-related risks and opportunities, serving as non-financial performance indicators analogous to traditional financial metrics like earnings or cash flow. However, ESG ratings are far from uniform: substantial variation exists across providers due to differences in measurement methodology, indicator selection, weighting schemes, and data sources. As a result, the same firm may receive divergent ESG scores from different agencies, raising important concerns about the reliability and comparability of ESG ratings in both investment decision-making and academic research.

to firms with stronger institutional connections. This measurement inconsistency raises concerns among investors.

The uncertainty introduced by ESG rating divergence poses challenges for a broad range of decision-makers, including investors, regulators, and corporate managers. This issue has been explored extensively in prior research (Chatterji et al. (2016); Gibson Brandon, Krueger, and Schmidt (2021) Gibson Brandon, Krueger, and Schmidt (2021); Christensen, Serafeim, and Sikochi (2022)). Christensen, Serafeim, and Sikochi (2022) present a counter-intuitive finding: greater ESG disclosure leads to greater ESG rating disagreement. Their research shows that ESG raters disagree more on outcome-based ESG metrics (e.g., carbon emissions, diversity performance) than on input-based metrics (e.g., corporate policies). Additionally, disclosure seems to amplify disagreements more for ESG outcomes, suggesting that while greater transparency is generally encouraged, it may not necessarily lead to greater consensus in ESG evaluations. Contradicting these results, Avramov, Cheng, et al. (2022) show that ESG rating uncertainty increases perceived market risk, raises the required risk premium, and lowers investor demand. These insights suggest that the equilibrium effects of ESG ratings should not be confined to a static setting. Instead, it is crucial to explore a multi-period dynamic framework in which market ESG factors evolve over time. This dynamic approach would allow for time-varying ESG risk premia and could potentially introduce an incremental asset pricing factor, further shaping investment behaviour and market outcomes.

Berg, J. F. Kölbel, and Rigobon (2022) show that ESG ratings contain substantial measurement error, making individual scores noisy proxies for corporate sustainability. They tackle this as a classical errors-in-variables problem by instrumenting one agency's rating with those of several others, requiring data from at least three providers, an approach that is difficult to implement in settings like ours with only two rating sources. Applying their correction to stock returns and profitability, they estimate noise-to-signal ratios by agency and find that their procedure outperforms simple averaging or PCA, yielding a stronger positive association between ESG performance and stock returns and confirming that green stocks outperform brown stocks. Overall, their results suggest that while single-provider ESG scores are unreliable, aggregating multiple ratings can recover a more precise measure of ESG performance.

Building on this insight, we aim to improve ESG measurement by combining data from two ESG rating providers - Refinitiv and Bloomberg. Intuitively, aggregating ratings from different sources, each relying on distinct methodologies and information sets, allows us to filter out idiosyncratic noise and extract a more accurate signal of unobservable ESG performance. This issue of attenuation bias is pervasive in the ESG literature, affecting not only regressions on stock returns but also studies examining accounting performance, cash flows, and other financial outcomes. By addressing this bias, our study contributes to a more precise understanding of the role of ESG factors in financial markets.

Several theoretical frameworks incorporate ESG preferences into asset pricing. To our knowledge, Pástor, Stambaugh, and Taylor (2021) and Pedersen, Fitzgibbons, and Pomorski (2021) are among the first to rigorously explore equilibrium asset pricing in the presence of ESG-driven investor preferences. Their models demonstrate how such preferences can shift the efficient frontier and influence expected returns. However, both studies treat ESG scores as exogenous and fully observable, effectively assuming a consensus on firms' ESG profiles. In practice, this assumption is contentious, as ESG ratings are subject to considerable divergence and measurement noise. The link between ESG performance and stock returns remains a topic of ongoing empirical and theoretical debate. One theoretical argument posits that green stocks attract heightened investor demand, which inflates prices and compresses expected returns (Pástor, Stambaugh, and Taylor (2021)[4]). On the empirical side, several studies document the outperformance of high-ESG firms, attributing this trend to increased attention to climate risk and the surge in capital flows into ESG-oriented funds (Van der Beck (2021); Pástor, Stambaugh, and Taylor (2022); G Andrew Karolyi, Ying Wu, and Xiong (2023)).

Other scholars have explored the role of ESG at the macro-financial level. Dimson, Karakaş, and X. Li (2015) show that successful ESG engagements can lead to reduced stock return volatility, suggesting a stabilising effect on financial markets. Expanding this analysis to the global scale, G Andrew Karolyi, Ying Wu, and Xiong (2023) examine both time-series and cross-sectional variations in international stock returns. They find robust evidence that green stocks tend to outperform brown stocks globally, with the outperformance largely driven by weaker returns in energy firms rather than stronger returns in technology sectors. These studies collectively highlight that ESG considerations can have significant implications not only for individual firms but also for broader asset pricing and market stability. Similar, Avramov, Lioui, et al. (2025) proposes a dynamic equilibrium model and show that risk premia entailed from ESG supply

[4] Recent work by Pástor et al. (2021b) draws a critical distinction between ex ante expected returns and ex post realised returns, demonstrating that U.S. green stocks outperformed brown stocks over the past decade primarily due to unexpectedly strong increases in environmental concerns. Their findings suggest that this outperformance was not fully anticipated by the market, implying that realised returns were influenced by unanticipated shifts in investor sentiment and evolving regulatory landscapes. This insight highlights the importance of accounting for dynamic ESG preferences and suggests that, over longer horizons, the equilibrium effects of ESG risk pricing may be more pronounced than those identified in static or full-sample analyses.

and demand shocks could offset a negative ESG-expected return relation in a static environment. According with the authors, the ESG rating divergence in equilibrium asset pricing in both the aggregate market and the cross section, and they advocate for the importance of considering rating disagreement when analysing sustainable investing. They show that ESG rating is negatively associated with future performance when there is little disagreement, and that the ESG-performance relationship could be insignificant or positive when disagreement increases. Their findings suggests that the lack of consistency in ESG ratings could distort the risk-return trade-off and reduce economic welfare. All of these studies suggests that ESG should have a role in the broader economy, but the extend of this role is still unknown. In this research we intend to contribute to this role.

More recently, Chu et al. (2020) find that a higher ESG index level can serve as a favourable signal of aggregate firm fundamentals, which is not immediately reflected in prices, leading to higher future market returns. While higher ESG demand may reduce expected returns in a cross-sectional setting, the authors argue that this pattern does not hold in a time-series context. According with Chu et al. (2020) the relationship ESG predictors and stock returns may not immediately clear. ESG activities may divert firms from maximizing shareholders value that results in an increase in costs that leads to a negative relationship between ESG and stock returns. However, firms' involvement in good ESG activities may benefit firms by improving their culture, reputation and human capital indicating a positive relationship between ESG performance and stock returns. Due to these ambiguous possibilities and limitations in terms of data, few studies examine the collective power of various ESG information on the aggregated stock market. Our work builds on Chu et al. (2020). Similar to their approach, we extract the ESG-driven return component by projecting firm-level excess returns onto their ESG scores. This component, free from noise, serves as input to a time-varying dynamic factor model (tvGDFM) following Barigozzi, Hallin, et al. (2021) to analyse ESG connectedness over time and frequency.

A related strand of the literature motivates the methodological use of connectedness and time-frequency tools. Although not written in an ESG setting, Umar, Gubareva, and Teplova (2021) is frequently cited as an important precursor because it shows how wavelet-based time-frequency methods can distinguish short-, medium-, and long-horizon transmission mechanisms in periods of systemic stress. Studying commodity-market volatility during the COVID-19 shock, the authors show that dependence varies across frequencies and over time, implying that aggregate connectedness measures can conceal economically distinct channels of adjustment. This insight is directly relevant for ESG research, where the pricing of sustainability-related information is also unlikely to be homogeneous across horizons. In this sense, the time-frequency perspective adopted in the present chapter builds on a broader literature showing that connectedness is not a static object, but one whose interpretation depends on whether shocks are transitory, medium-term, or persistent.

More directly in the ESG literature, Wan, Yin, and You Wu (2024) examine return and volatility connectedness across eleven global ESG stock indices using a TVP-VAR time-frequency framework. Their evidence shows strong cross-market spillovers, with Europe and North America acting mainly as net transmitters and several Asia-Pacific markets acting mainly as net receivers. Importantly for our argument, they find that return connectedness is concentrated at high frequencies, whereas volatility connectedness is concentrated at low frequencies, and that both forms of connectedness intensify during major stress episodes, especially the COVID-19 period. This contribution is important because it demonstrates that ESG-related spillovers are both time-varying and frequency-specific, thereby providing direct support for modelling ESG information through a dynamic connectedness framework rather than through static correlations or raw index levels alone. Our study extends this logic from the connectedness of aggregate ESG stock indices to the connectedness embedded in firm-level ESG information and its return-predictive content.

Recent work also broadens the asset-pricing scope of ESG connectedness beyond ESG equity indices alone. For example, Abdelkader and Si Mohammed (2025) studies dynamic connectedness among ESG, brown, and AI-related assets over 2017-2025 and emphasizes that spillovers differ between contemporaneous and lagged channels under changing market and geopolitical conditions. This line of research reinforces the idea that ESG should be analysed as part of a broader network of financial transmission rather than as an isolated characteristic observed at the firm level. It also supports the interpretation that ESG-linked shocks can propagate across asset classes and sectors in ways that evolve over time. Relative to this literature, our contribution is to show that such connectedness is not only present at the index or cross-asset level, but can also be decomposed within firm-level ESG information into short- and long-frequency components with distinct implications for expected returns and firm fundamentals.

Moreover, strong ESG performance can enhance a firm's reputation, sending positive signals to investors and other stakeholders (Tamimi and Sebastianelli (2017)). At the same time, high-quality ESG disclosure helps mitigate information asymmetry between firms and investors, enabling a clearer assessment of firm-level risks and opportunities (Dhaliwal et al. (2011)). This reduction in informational opacity facilitates more informed investment decisions and can increase investor confidence. As a result, superior ESG performance not only supports a firm's long-term sustainability but also attracts greater interest from foreign institutional investors, who may otherwise face significant barriers when evaluating firms with limited ESG transparency. Pástor, Stambaugh, and Taylor (2021) developed a dynamic asset pricing model in which firms vary in the sustainability of their operations, ranging from "green" (positive externalities) to "brown" (negative externalities), and investors exhibit heterogeneous ESG preferences. These preferences include a direct utility from holding green assets, concern for aggregate social impact, and in an extended version, sensitivity to climate risk. Their model shows that investors with stronger ESG preferences are willing to pay a premium for green assets, leading to lower expected returns for these assets (negative CAPM alphas) and higher costs of capital for brown firms. Despite earning lower returns, ESG-minded investors are compensated through non-financial utility, thus explaining the pricing effects of sustainability in equilibrium.

Our paper contributes to the growing literature on climate change and its financial market implications (Giglio, Kelly, and Stroebel (2021)). A notable strand of this literature explores how climate-related information is priced into asset returns. For example, R. F. Engle et al. (2020) propose a dynamic hedging strategy for climate risk, extracting innovations from climate news through textual analysis of major newspapers. Their approach highlights how market participants respond to evolving climate narratives. Similarly, Ardia et al. (2023) construct a Media Climate Concern Index based on climate-related news coverage from leading U.S. newspapers and newswires. They show that unexpected increases in climate concern led to higher stock prices for green firms and lower prices for brown firms, underscoring the asymmetric impact of climate news on different types of firms. Together, these studies emphasise the role of media sentiment and information flows in shaping the pricing of climate-related risks in equity markets.

In addition, Gospodinov, Gaffney, and Ng (2025) provide a compelling contribution to the climate-economics literature by emphasising the importance of frequency decomposition in environmental data analysis[5]. Using panel datasets for 48 U.S. states and 50 countries, the authors extract both low- and high-frequency components of temperature

[5]Gemenne et al. (2014) argue that analysing long-span data may be subject to a "frequency identification trade-off," whereby societal changes may occur more rapidly than low-frequency variations in climate, potentially complicating causal inference. Their critique highlights that the challenge lies not only in capturing low-frequency environmental trends but also in ensuring temporal relevance in a rapidly evolving socio-economic context. More broadly, their work contributes to the expanding literature demonstrating that climate influences security outcomes across both historical and contemporary periods. This influence is observed globally, spans both rapid and gradual climatic events, and manifests across diverse forms of conflict at multiple spatial scales.

fluctuations and investigate their distinct effects on economic outcomes. One of their key findings is that the low-frequency component of temperature has exhibited a persistent upward trend since the 1970s coinciding with the well documented global slowdown in economic growth. This observation motivated their use of a regression framework that accommodates heterogeneous effects of low- and high-frequency temperature variations, allowing for differential responses to common business cycle shocks. Their results suggest that high-frequency temperature fluctuations may exert marginally significant effects on growth, while the role of low-frequency changes remains more ambiguous. The study underscores the necessity of accounting for temporal structure in environmental variables, a perspective that we extend to ESG performance in financial markets. Like temperature, we argue that ESG signals contain both transitory (high-frequency) and persistent (low-frequency) components, which may exert distinct and time-varying influences on firm performance and systemic financial interconnectedness.

Overall, the existing literature highlights the complex and evolving relationship between ESG performance and stock returns, with mixed empirical evidence on whether ESG factors enhance or reduce financial performance. While some studies suggest that green stocks attract investor demand and experience positive abnormal returns, others point to the risks of ESG rating divergence, measurement inconsistencies, and potential mispricing due to investor sentiment and regulatory pressures. A key challenge in this field is the noise and disagreement in ESG ratings, which can obscure the true relationship between ESG performance and financial outcomes. Building on this body of work, our research aims to contribute by addressing the issue of ESG rating divergence and measurement error through a multi-source approach. By focusing on the dynamic structure of ESG-driven returns and leveraging spectral methods to decompose short- and long-term connectedness, our study offers a novel contribution to understanding how ESG signals shape systemic risk and financial interconnectedness in green and brown firms. This study not only enhances our understanding of how ESG factors influence asset pricing but also provides insights into the role of ESG information in investment decision-making and corporate policies.

3.3 Methodology

To examine whether ESG scores embed a meaningful and persistent financial signal and to assess whether this signal differs between brown and green firms our empirical strategy proceeds in two key stages. We combine firm-level excess return decomposition with dynamic factor modelling and frequency-domain analysis, enabling us to isolate the ESG-driven component of returns and trace its interconnectedness over time and across investment horizons.

3.3.1 Decomposing Excess Returns into ESG-Driven Components

In the first stage of our empirical strategy, we isolate the component of excess returns at the firm level that is systematically driven by the performance of ESG. Following the framework of Chu et al. (2020), we estimate a series of time-series regressions at the firm level, where the dependent variable is the monthly excess return for each firm, and the independent variable is the firm's own ESG score.

As highlighted above, to enhance the robustness of our ESG measure, we construct a composite ESG score by averaging the scores provided by two widely used and methodologically distinct ESG data vendors: Refinitiv and Bloomberg. Unlike Chu et al. (2020), who emphasise changes in ESG at the aggregate level (i.e., ESG growth), our focus lies in the absolute level of ESG performance at the firm level. This decision aligns with our objective of capturing persistent ESG effects, particularly those that manifest over longer horizons and are more suited to analysis using frequency domain methods.

By incorporating the raw ESG score into the asset pricing framework, we aim to identify whether firms with higher (or lower) ESG performance exhibit systematically different return dynamics. This specification is better suited to uncovering the structural role of ESG in firm valuation, especially in the context of long-term sustainability considerations. Crucially, rather than assuming a constant relationship between ESG scores and returns, we allow the slope coefficient to vary over time. That is, the effect of ESG on returns is both firm-specific and time-varying, accommodating evolving market perceptions of ESG relevance.

For each firm i, we estimate the following predictive regression on ESG scores over time t:

$$\text{ExcessReturn}_{i,t} = \alpha_{i,t} + \beta_{i,t} \cdot \text{ESG}_{i,t} + \varepsilon_{i,t} \tag{3.1}$$

where $\text{ExcessReturn}_{i,t}$ denotes the excess return of firm i at time t; $\text{ESG}_{i,t}$ represents the average ESG score of firm i at time t, compute as the mean of Refinitiv and Bloomberg ESG ratings; $\beta_{i,t}$ captures the sensitivity of firm i's excess returns to its ESG performance; and $\varepsilon_{i,t}$ is the regression residual, representing the portion of return variation not explained by ESG.

In this specification, our primary focus is on the estimate of β (denoted $\hat{\beta}$). Additionally, the null hypothesis is that ESG scores have no predictive power for excess returns, i.e., $\beta = 0$. The alternative hypothesis posits that $\beta \neq 0$, suggesting that ESG scores contain information relevant to explaining return dynamics. To assess statistical significance, we compute the t-statistics for $\hat{\beta}$ using heteroskedasticity-and autocorrelation-consistent (HAC) standard errors, as proposed by Newey and West (1987).

The ESG-driven component of returns is then given by the time-varying fitted value:

$$\widehat{R}_{i,t}^{\mathrm{ESG}} = \hat{\beta}_{i,t} \cdot \mathrm{ESG}_{i,t} \tag{3.2}$$

This term captures the portion of return dynamics that can be systematically attributed to ESG signals, effectively filtering out idiosyncratic noise and other non-ESG-related fluctuations. The resulting matrix of fitted values, denoted as $\widehat{R}_{i,t}^{\mathrm{ESG}}$ for each firm i and time t, serves as the core input for our subsequent analysis using the time-varying General Dynamic Factor Model (tvGDFM) and spectral connectedness measures, using the methodology proposed by Barigozzi, Hallin, et al. (2021).

This new panel of ESG-driven excess returns forms a de-noised, high-signal dataset that reflects the component of financial performance most closely linked to ESG fundamentals. By isolating this ESG-relevant return variation across firms and over time, we create a more reliable basis for investigating how ESG risks and opportunities propagate through financial markets. This filtered matrix enhances our ability to detect persistent structures and interconnected dynamics, shedding light on the long-term channels through which ESG considerations influence asset prices and systemic risk.

3.3.2 Modelling ESG Connectedness with a Time-Varying General Dynamic Factor Model

In the next stage of our empirical strategy, we apply the Time-Varying General Dynamic Factor Model developed by Barigozzi, Hallin, et al. (2021) to the matrix of ESG-driven excess returns, then compute the connectedness measures as described bellow. This model enables us to uncover a small number of latent dynamic factors that capture the common variation across firms' ESG-related return components. By estimating the model in rolling windows, we allow for time-varying dynamics in both the factor structure and the exposure of firms to ESG shocks, aligning with the inherently evolving nature of ESG materiality over time.

The tvGDFM offers a major methodological advantage through its operation in the frequency domain Barigozzi, Hallin, et al. (2021), allowing us to disentangle short-term (high-frequency) and long-term (low-frequency) connectedness. This spectral decomposition is especially well-suited to our objective: identifying persistent ESG spillovers and understanding how sustainability risks become embedded in asset prices over extended horizons. The low-frequency connectedness in particular reflects long-run structural dependencies, which are central to assessing systemic ESG impacts. This methodological approach is grounded in an important line of research that applies frequency-domain analysis to econometric modelling. The use of band-limited estimators has a long history, beginning with the foundational work of Hannan (1963) and Hannan (1965), who introduced the idea of estimating distributed lag models within specific frequency bands. A particularly relevant antecedent is the seminal contribution of R. F. Engle (1974), who developed the concept of band spectrum regressions. R. F. Engle (1974) framework restricts standard least squares estimation to a subset of frequencies in order to examine whether slope coefficients vary across the frequency domain.

In the context of our analysis, this tradition underpins the spectral decomposition employed in the Time-Varying General Dynamic Factor Model, Barigozzi, Hallin, et al. (2021). By estimating the dynamic factor structure over selected frequency bands, low for long-run trends and high for short-term fluctuations, we can isolate and interpret horizon-specific ESG driving components. This band-specific focus enhances our ability to distinguish between persistent structural dependencies and transitory ESG dynamics, a distinction that is central to understanding the temporal nature of sustainability risks in financial markets.

To implement the frequency-domain analysis, we begin by estimating the spectral density matrix of the firm ESG-driven return series. The estimator is given by:

$$\widehat{\Sigma}^X_{n,T}(t/T;\theta_j) = \frac{1}{2\pi M_T} \sum_{\ell=-m_T}^{m_T} \left(1 - \frac{|\ell|}{m_T}\right) \sum_{s=t-M_T/2+1+\ell}^{t+M_T/2} X^X_{n,s-\ell} e^{-i\ell\theta_j}, \tag{3.3}$$

where $\theta_j = \pi j/m_T$, $|\ell| \leq m_T$, and M_T defines the smoothing window. We set $M_T = 22$, corresponding to a trading month, and $m_T = 5$, representing one week of trading days. The kernel-based smoothing in this step ensures reliable estimation of the time-localised spectral density.

The impulse response functions are then approximated by truncating the infinite lag structure at a maximum lag $k_{\max}$, such that the estimated filter entries are:

$$\hat{c}_{ij,n,T}(t;L) = \sum_{k=0}^{k_{\max}} \hat{c}_{ijk,n,T}(t)L^k, \quad 1 \le i \le n, \quad 1 \le j \le q. \tag{3.4}$$

We set $k_{\max} = 22$ to truncate the impulse response functions at a sufficient lag length, ensuring that the dynamic effects of ESG shocks are adequately captured over time without introducing excessive noise.

Once the spectral density matrix is estimated, the number of dynamic factors q is determined following the information criterion proposed by Hallin and Liška (2007), as implemented in Barigozzi, Hallin, et al. (2021). This approach evaluates the local estimate of the spectral density and balances model fit with parsimony. Empirical results across multiple time points consistently support the presence of $q = 2$ factors throughout the sample period, validating the assumption of a time-invariant factor structure. The estimation frequency (skip parameter) is set to 3 months, allowing us to monitor the evolution of ESG-driven return dynamics over the 2010–2024 period. This choice provides a meaningful trade-off between capturing high-resolution time variation and maintaining computational tractability.

To formalise our connectedness measurements, we follow the framework of Diebold and Yılmaz (2014) and construct $n \times n$ connectedness matrices based on the estimated spectral density components of the common ESG-driven shocks. Specifically, the connectedness matrix at time t and frequency z is defined as:

$$\widehat{Q}_n(t;z) := \widehat{C}_n(t;z)\widehat{C}'_n(t;z), \quad \frac{M_T}{2} \le t \le \left(T - \frac{M_T}{2}\right), \quad z \in \mathcal{C} \tag{3.5}$$

where $\widehat{C}_n(t;z)$ denotes the matrix of estimated spectral components at time t and frequency z. Owing to its quadratic form, $\widehat{Q}_n(t;z)$ is invariant to the sign indeterminacy that typically arises in the estimation of factor loadings.

In summary, to capture the dynamics of ESG connectedness across distinct investment horizons, we adopt a frequency-domain approach based on the methodology developed by Barigozzi, Hallin, et al. (2021), which we adapt to monthly data using a more macroeconomically meaningful frequency band decomposition. The connectedness matrix, denoted as $\widehat{Q}_n(t;z)$, is evaluated across two spectral bands, allowing us to disentangle the transitory from the persistent components of ESG spillovers. In particular, the long-term connectedness, $\widehat{Q}_n(t;1)$, is estimated over the low-frequency band $z \in [0, 0.105]$[6] radians[7]. This component captures slow-moving ESG forces, such as structural regulation, strategic corporate adaptation, and long-run investor preferences. In contrast, the short-term connectedness, $\widehat{Q}_n(t;3)$, is computed over the high-frequency band $z \in [0.524, \pi]$ radians, which reflects immediate market reactions to ESG news, sentiment shocks, and transient ESG-related events.

For each point in time t, we extract time-varying connectedness matrices to characterize the systemic interactions of ESG-related shocks. The matrix $cctlong_t$ summarises persistent ESG spillovers across firms, while $cctshort_t$ captures high-frequency ESG dynamics that dominate in the short run. To quantify the aggregate evolution of ESG systemic risk, we compute spectral connectedness indices as the Frobenius norms of these matrices. Specifically, the Total Long-Term ESG Connectedness Index, $athlong_t$, measures the magnitude of structural and persistent ESG interdependencies, whereas the Total Short-Term ESG Connectedness Index, $athshort_t$, captures transient interactions that are more sensitive to market sentiment and ESG news flows. These indices offer a frequency-resolved representation of ESG-related systemic risk, enabling us to track how ESG spillovers propagate over time and to assess whether markets respond differently to short-lived versus enduring ESG signals.

To complement this aggregate analysis, we further decompose connectedness at the firm and sector levels to identify heterogeneous patterns across industries. This decomposition allows us to explore lead-lag relationships and uncover whether ESG shocks originate in specific sectors before propagating more broadly. By focusing on the frequency-specific behaviour of ESG connectedness, we aim to provide a more granular understanding of how ESG information is incorporated into asset prices across different investment horizons.

Our empirical analysis relies on a balanced panel of 334 U.S. firms, comprising 167 brown firms, primarily from energy and energy-intensive industries, and 167 green firms, selected based on their top-quartile ESG scores according to Refinitiv. These sectors are

[6]Following S. Li (2023), who defines distinct spectral bands to isolate low-frequency risk components, we adopt a similar rationale grounded in macro-financial theory. Specifically, our chosen long-term frequency band $[0, 2\pi/60]$ radians corresponds to cycles of 5 years or longer, aligning with the business-cycle-frequency (BCF) range of 1.5 to 8 years (18 to 96 months) used in his study. This choice allows us to capture persistent, structural ESG dynamics, such as those associated with climate transition risks, while the short-term band $[2\pi/12, \pi]$ captures transitory, high-frequency ESG spillovers.

[7]While the business-cycle frequency (BCF) band is typically defined as cycles between 1.5 and 8 years (as in S. Li (2023)), our sample spans only 14 years of monthly data. Estimating connectedness dynamics beyond 5-year cycles would exceed the data's effective horizon and reduce statistical reliability. Therefore, we restrict the long-term band to frequencies corresponding to cycles of 5 years or longer ($z \in [0, 2\pi/60]$), which balances the need to capture persistent ESG risks with the limitations of the available sample.

particularly suitable for studying ESG transmission due to their differential exposure to regulatory, environmental, and reputational risks, which makes them central to the debate on sustainability and financial stability. The contrasting characteristics of green and brown firms also provide a natural laboratory for testing whether ESG-related pricing signals are firm-type dependent and whether they evolve differently across short- and long-term horizons.

3.3.3 Return Prediction Models

In-Sample Performance

To assess the predictive power of ESG connectedness across different frequencies, we estimate a series of in-sample predictive regressions of future excess market returns on our ESG connectedness matrix. This framework follows the approach of Chu et al. (2020), adapted to our context.

The baseline predictive regression takes the form:

$$r_{t \to t+h} = \alpha_h + \beta_h \, ESG_t + \varepsilon_{t+h}, \tag{3.6}$$

where $r_{t \to t+h} = \frac{1}{h} \sum_{j=1}^{h} r_{t+j}$ denotes the h-month ahead cumulative excess return, constructed as an overlapping average. ESG_t denotes the ESG connectedness index at time t, computed from one of two distinct frequency bands[8]. α_h and β_h are horizon-specific intercept and slope coefficients, and ε_{t+h} is the regression residual.

The connectedness predictors ESG_t are computed using a time-varying general dynamic factor model (tv-GDFM), applied to firm-level ESG-driven return components. Spectral decomposition is performed to separate the signal across macro-economically meaningful frequency bands, as described in Section 3.2.

We estimate this model over a range of forecast horizons $h \in \{1, \dots, 24\}$, corresponding to monthly returns from 1 up to 24 months ahead. To ensure only information available at time t is used, we lag the ESG connectedness predictors by h periods.

Estimation Procedure: To address serial correlation and heteroskedasticity induced by overlapping returns, we compute Newey–West heteroskedasticity and autocorrelation-consistent (HAC) standard errors with lag length 7. For each predictor[9] and horizon, we

[8] ESG_t^{short}: Short-term (high-frequency) ESG connectedness, capturing cycles with periods of up to 1 year ($z \in [0.524, \pi]$ radians); ESG_t^{long}: Long-term (low-frequency) ESG connectedness, representing persistent dynamics with cycles no longer than 5 years ($z \in [0, 0.105]$ radians).

[9] The three connectedness indices used as predictors are defined as: $\texttt{ath\_short}_t$: short-term ESG connectedness index (high-frequency), integrated over cycles $\leq$ 1 year; $\texttt{ath\_long}_t$: long-term ESG

report the estimated slope coefficient $\hat{\beta}_h$, the corresponding t-statistic, and the in-sample R_h^2 statistic, computed as:

$$R_h^2 = 1 - \frac{\mathrm{Var}(r_{t\to t+h} - \hat{r}_{t\to t+h})}{\mathrm{Var}(r_{t\to t+h})}. \tag{3.7}$$

These indices allow us to evaluate the predictive content of ESG risk propagation at different temporal horizons, distinguishing transitory from persistent sources of return predictability.

3.4 Data

To address our research question, whether ESG measures contain an informative signal beyond noise, particularly in their long-run component, we compile a comprehensive dataset covering U.S. firms across various sectors. Firms are selected based on their Standard Industrial Classification (SIC) codes and categorised into two distinct groups: brown and green firms in accordance with the information provided by Refinitiv.

The brown firm group comprises 167 U.S. companies, primarily from the energy sector and other highly energy-dependent industries. These firms are especially relevant for ESG analysis due to their elevated exposure to environmental risks, regulatory scrutiny, and carbon transition challenges. ESG considerations are increasingly material for their financial performance, cost of capital, and market valuation. The energy sector's direct link to carbon emissions and climate policy makes it a focal point for ESG investing and sustainable finance research.

The green firm group also consists of 167 U.S. companies, selected based on their ESG performance. Specifically, we identify firms whose Refinitiv ESG Combined Scores fall within the third or fourth quartiles in the most recent fiscal year. Refinitiv ESG Combined Score is a widely used aggregate metric ranging from 0 to 100, with higher scores reflecting better environmental, social and governance practices. Firms scoring above the median are considered to be relatively strong ESG performers within the U.S. market. By applying this selection criterion, we ensure the inclusion of companies that are positively distinguished for their ESG profiles.

A central input for our analysis is the firm-level ESG score data, collected at a monthly frequency. Given the well-documented divergence among ESG rating providers, we enhance the robustness and reliability of our ESG measure by combining data from

connectedness index (low-frequency), associated with persistent ESG spillovers.

two leading agencies: Refinitiv[10] and Bloomberg[11]. These providers adopt distinct methodologies, utilise different data sources, and apply varying weighting schemes in their ESG assessments. To mitigate provider-specific biases and reduce measurement error, we construct a composite ESG score by averaging the ESG combined scores from both sources for each firm and month.

This multi-source approach serves to attenuate the idiosyncratic noise that often characterises single-provider ESG measures, improving the precision of our estimates. It also addresses the well-known issue of attenuation bias, a widespread challenge in ESG research that can distort the estimated relationships between ESG performance and financial outcomes such as stock returns, accounting metrics, and firm risk. By integrating Refinitiv and Bloomberg data, we aim to capture a more accurate and consistent signal of a firm's true ESG profile across time. This strategy is particularly important in light of evidence from Berg, J. F. Kölbel, and Rigobon (2022), who show that ESG ratings from major providers often differ significantly, reflecting fundamental disagreements on what constitutes ESG performance and how it should be measured.

A fundamental component of our dataset is firm-level return information and firms fundamentals, which we obtain from the Center for Research in Security Prices (CRSP[12]) database via the WRDS platform. To isolate the portion of returns attributable to firm-specific and ESG-related factors, we compute excess returns by subtracting the risk-free rate from the total return. The risk-free rate is sourced from the Fama-French dataset, specifically based on the return of one-month U.S. Treasury bills, also accessed via WRDS.

Since firm-level ESG scores have only become widely available in recent years, our sample spans from January 2010 to December 2024, totalling 180 monthly observations ($T = 180$). This time-frame strikes a balance between data availability and analytical depth, allowing for robust empirical investigation into the evolving role of ESG fac-

[10]ESG Combined Score (Refinitiv): Refinitiv ESG Combined Score measures a company's overall ESG performance by integrating its ESG performance score with its ESG controversy score. The scores are ranked from 0 to 100, with 0 being the poor performance and 100 the excellent ESG performance. ESG Performance Score evaluates a company's relative performance across environmental, social, and governance dimensions based on publicly available information. The ESG Controversy Score adjusts the performance score downward to reflect controversies that can negatively impact the company's ESG reputation.

[11]ESG Disclosure Score (Bloomberg): A proprietary Bloomberg score that assesses the extent of a company's ESG data disclosure. This score ranges between 0 to 100. With 0 no ESG disclosure, and 100 representing full disclosure of all ESG data points tracked by Bloomberg. The score aggregates disclosed ESG data using a consistent framework across sectors and regions. Environmental (E), Social (S), and Governance (G) pillars are equally weighted.

[12]CRSP provides comprehensive and high-quality data on U.S. equity returns, widely used in empirical finance. The return variable used in our study reflects the percentage change in the total value of an investment in a firm's common stock over a given period, expressed per dollar of initial investment.

tors in financial markets. The period encompasses major sustainability-related policy developments, shifts in investor preferences, and macroeconomic shocks.

A central element of our study is the decomposition of ESG-driven return dynamics across different frequencies. As such, we emphasise the importance of distinguishing low-frequency (persistent) from high-frequency (transitory) variations in ESG signals. While a time series with $T = 180$ could be generated from different configurations of sampling frequency and temporal coverage, we interpret our monthly dataset as a signal composed of orthogonal components, each corresponding to variations with distinct periodicities. This frequency-domain approach enables us to disentangle short-term ESG fluctuations, often tied to news shocks or regulatory announcements, from more persistent ESG trends that reflect long-run corporate strategy and sustainability integration. This decomposition provides a nuanced understanding of how ESG information is transmitted across firms and over time, contributing to more accurate assessments of systemic ESG risk and return predictability.

3.5 Empirical Results

This section presents the main findings from the time-varying ESG connectedness measures, highlighting how ESG spillovers evolve across different frequencies and firm types. Figures 1 and 2 illustrate the temporal dynamics of short-term and long-term ESG connectedness for green firms, while Figures 3 and 4 depict the corresponding patterns for brown firms. By comparing these frequency-specific connectedness measures over time, we uncover how ESG systematic risk signals propagate differently across frequencies. These dynamics provide crucial insights into the role of ESG information in shaping firm-level interconnectedness and its potential implications for asset pricing across green and brown firms.

[**Figure C.1 to Figure C.4 around here**]

Figures C.1 and C.2 illustrate the evolution of short-term and long-term ESG connectedness among green firms between 2013 and 2021, revealing clear temporal patterns consistent with major policy and market events[13]. In the short term (Figure C.1), pronounced spikes are visible in 2013–2014, 2017, and 2020–2021, indicating periods of intensified market reactions to ESG-related developments. These transitory shocks likely stemmed from regulatory announcements, such as the European Commission's Action Plan on Financing Sustainable Growth (2018), the growing adoption of the Task Force on Climate-related Financial Disclosures (TCFD) frameworks (established in 2015 and widely adopted from 2017 onward)[14], and BlackRock's high-profile commitment to climate risk integration (January 2020)[15] increased investor scrutiny of firms' climate strategies, amplifying ESG return co-movements among leaders in sustainable practices. The EU Green Deal (2019)[16] and the surge in climate activism, including youth-led

[13]The following major climate-related events are highlighted in the analysis: (1) U.S. Clean Power Plan announcement (June 2, 2014); (2) UN Climate Summit (September 23, 2014); (3) Paris Agreement adoption (December 12, 2015); (4) Trump elected (November 8, 2016); (5) U.S. Paris withdrawal announcement (June 1, 2017); (6) EU Sustainable Finance Action Plan launch (March 8, 2018); (7) U.S. Climate Assessment Report release (November 23, 2018); (8) Formal U.S. withdrawal notice from Paris (November 4, 2019); (9) BlackRock's climate investment pledge (January 14, 2020); (10) Biden elected (November 3, 2020); (11) U.S. officially rejoins Paris Agreement on inauguration day (January 20, 2021); and (12) Formal re-entry into the Paris Agreement (February 19, 2021).

[14]The TCFD was launched by the Financial Stability Board in December 2015, with recommendations published in June 2017. By 2018–2019, major corporations and institutional investors had begun adopting the framework, standardising climate risk disclosure and influencing capital allocation decisions.

[15]In his annual letter to CEOs, published in January 2020, BlackRock's CEO Larry Fink announced that climate risk would become a defining factor in the firm's investment strategy, committing to exit thermal coal investments and integrate sustainability across 7 trillion dollars of assets under management.

[16]The European Green Deal, announced by the European Commission in December 2019, set the goal of making Europe the first climate-neutral continent by 2050. This policy framework has pushed EU member states to adopt green growth strategies, aligning economic recovery with environmental

movements like Fridays for Future (founded in 2018)[17], further amplified sustainability discourse, triggering stronger ESG-related interdependence across green firms. This aligns with Chu et al. (2020), who argue that aggregate ESG signals exert forward-looking influence on market returns during periods of heightened environmental concern. Despite these spikes, the median connectedness remains comparatively stable, suggesting that only subsets of green firms exhibited strong short-run co-movements, while others reacted more moderately to transitory ESG news.

Long-term ESG connectedness among green firms (Figure C.2) presents a different dynamic, characterised by a stable upward trajectory, especially during 2014–2017 and 2018–2020. Peaks in 2017 and 2021 coincide with periods of major global policy milestones, including the withdrawal of U.S. from the Paris Agreement and broader institutionalisation of ESG disclosure norms. These trends suggest that green firms progressively integrated ESG considerations into strategic decision-making, leading to a more systemic and persistent inter-firm alignment. This is consistent with G Andrew Karolyi, Ying Wu, and Xiong (2023) and Pástor, Stambaugh, and Taylor (2021), who emphasise that ESG fundamentals are increasingly embedded into firm value propositions and are rewarded over longer horizons.

Figures C.3 and C.4 shift the focus to brown firms, revealing a sharper and more volatile short-term ESG connectedness (Figure C.3), with notable peaks in 2013, 2015, 2016, 2019, and 2021. These short-run fluctuations reflect heightened sensitivity to regulatory and policy shocks, such as the U.S. Clean Power Plan announcement (2014) and the 2014 UN Climate Summit, which prompted significant investor reassessment of climate transition risks. This behaviour supports the findings of R. F. Engle et al. (2020) and Ardia et al. (2023), who document that high-emission and regulation-sensitive firms exhibit disproportionately strong responses to climate-related events due to elevated transition risks and divestment pressures. The broader confidence bands in early periods further underscore the heightened uncertainty surrounding ESG pricing for carbon-intensive firms during these regulatory shifts.

In contrast, long-term ESG connectedness for brown firms (Figure C.4) reveals a more gradual convergence toward stronger and more uniform ESG synchronisation, particularly peaking in 2020–2021. This shift suggests a structural adjustment toward climate-aligned strategies, consistent with Pástor, Stambaugh, and Taylor (2021), who argue that ESG

sustainability.

[17]Fridays for Future is a global movement started by Swedish climate activist Greta Thunberg in 2018. It quickly spread internationally, with students and youth groups organizing regular protests and demanding urgent action on climate change. This increased societal pressure further propelled ESG discourse and policy action, influencing investor and corporate behaviour.

risk premia become more discernible at low frequencies as temporary shocks are filtered out. Compared to green firms, however, the long-term ESG integration of brown firms appears less smooth, reflecting the challenges these sectors face in transitioning to sustainable business models.

In addition, a notable difference emerges when comparing the distributional properties of ESG connectedness between green and brown firms. In Figures C.1 and C.2, which depict short-term and long-term ESG connectedness for green firms, the mean (red dashed line) is consistently far from the median (blue line), suggesting the presence of significant outliers[18] in the tails and an asymmetric distribution of ESG spillovers. This asymmetry likely reflects heterogeneous ESG integration across green firms, where a subset of firms, particularly those with stronger sustainability strategies or higher investor attention, drive pronounced co-movements, while others remain less affected. By contrast, Figures C.3 and C.4 for brown firms show a closer alignment between the mean and median, particularly in the long-term frequency, indicating a comparatively more symmetric distribution of connectedness. This suggests that ESG shocks, while impactful, are more uniformly transmitted across brown firms, likely due to their shared exposure to regulatory scrutiny, transition risks, and investor divestment pressures. The stronger asymmetry in green firms reinforces the idea that ESG dynamics are more firm-specific in sectors where sustainability strategies vary widely, whereas in brown

[18] Our diagnostics flagged the following green firms outliers: Commercial Metals Company (CMC), Tetra Tech, Inc., IDEXX Laboratories, Inc., Kimco Realty Corp., Acadia Realty Trust, CSG Systems International, Inc., Express-1 Expedited Solutions, Inc. (later XPO Logistics/XPO, Inc.), and Northern Trust Corp. To gauge whether these spikes plausibly map to climate-salient shocks, we reviewed dated ESG/climate disclosures and related controversies around the spike windows. Several clear episodes emerge. For example, for Northern Trust (asset-manager/custodian), the Australian Securities & Investments Commission issued greenwashing infringement notices on 19 December 2023 concerning statements about a carbon-emissions exclusion screen; the notice was resolved by payment without admission of liability. For CMC (EAF "green steel"), plant-level air-pollution penalties in New Jersey were recorded in 2013–2016, and in April 2016 Ector County and the TCEQ filed suit alleging improper disposal/unauthorized burning at a recycling site (as disclosed to the SEC; we did not locate a public final disposition). For Tetra Tech (environmental and resilience consulting), the Hunters Point remediation matter at subsidiary Tetra Tech EC produced criminal sentencing in May 2018 for falsified sampling, the U.S. Department of Justice's October 2018 decision to join whistleblower suits, and a partial civil settlement announced in January 2025 under the False Claims Act/CERCLA (with denial of liability and related civil matters ongoing). For Acadia Realty Trust (retail REIT), legacy New York remediation obligations include a July 24, 2014 Order on Consent at Farmingdale, a March 30, 2015 Record of Decision, and a March 2, 2016 environmental easement, alongside routine groundwater monitoring at a Brooklyn property, however, these do not involve misrepresentation claims. By contrast, for Kimco Realty, IDEXX, and CSG Systems we did not identify regulator-led greenwashing enforcement within our window. Taken together, these dated, firm-specific episodes provide plausible catalysts for the extreme short-horizon spikes we observe: climate- and ESG-related disclosures or controversies can transiently amplify connectedness for a subset of issuers while the broader cross-section remains comparatively unaffected. We do not claim causality, but the timing and nature of these events are consistent with the outlier behaviour.

sectors, systemic factors create a more homogeneous response pattern.

Overall, the comparison between green and brown firms, across different frequencies, underscores significant disparities in ESG dynamics. We observe distinct patterns for both short-term and long-term ESG connectedness, with green and brown firms following notably different trajectories. Green firms tend to exhibit more stable and persistent long-term ESG connectedness, reflecting an earlier and more consistent integration of sustainability considerations into their corporate strategies. In contrast, brown firms show a transition from reactive short-term ESG responses to more coordinated long-term alignment, likely driven by regulatory compliance, increasing investor pressure, and the gradual internalisation of transition risks. These findings resonate with the work of Avramov, Cheng, et al. (2022) and Bolton and Kacperczyk (2021), who highlight how ESG risk is priced differently across firm types due to sectoral characteristics, investor uncertainty, and varying disclosure practices.

Collectively, Figures C.1 to C.4 reveal that ESG signals propagate in a time- and frequency-dependent manner. Short-term fluctuations are predominantly influenced by regulatory or media-induced shocks, while long-term ESG connectedness reflects a more gradual strategic adaptation, with firms integrating sustainability into their long-term business models. These observations provide empirical support for the theoretical predictions of Chu et al. (2020) and Pástor, Stambaugh, and Taylor (2021), who argue that ESG factors have the most profound influence on fundamentals and risk premia over extended horizons. Moreover, our use of the frequency-domain approach proves indispensable in distinguishing between transitory noise and persistent ESG spillovers, offering a nuanced understanding of how sustainability factors are priced in financial markets. This aligns with the view that ESG information plays a pivotal role in asset pricing, as evidenced by the works of Ardia et al. (2023), Chu et al. (2020), Avramov, Lioui, et al. (2025), and Giglio, Kelly, and Stroebel (2021).

3.5.1 Predictive Power of ESG connectedness

In this section, we test the return-predictive content of a single, aggregate ESG connectedness index built by pooling green and brown firms. By construction, this index isolates the market-wide (systematic) component of ESG-related co-movement, an environmental facet of systematic risk, so any predictability we uncover reflects common, not idiosyncratic, ESG shocks.

This methodological shift is motivated by the conceptual distinction between cross-sectional and time-series predictability highlighted by Chu et al. (2020). In their study, the authors argue that aggregating green and brown firms in a time-series framework helps reveal systematic ESG risk, which may be obscured in cross-sectional designs. Specifically, they note that "the impact on cross-sectional returns from investors' demand shock due to unexpected climate change concerns can be mitigated by aggregating green and brown firms together" (Chu et al. (2020)). In other words, firm-specific shocks (such as investor reallocation between green and brown firms) can generate strong return dispersion across firms in the cross-section, but when firms are aggregated, these idiosyncratic effects may offset each other, suppressing the signal unless the ESG risk is truly systematic.

In cross-sectional frameworks, returns are compared between firms, often capturing transient or firm-specific ESG influences such as scandals, disclosures, or changing investor sentiment. However, time-series frameworks focus on how average market returns evolve over time, allowing us to assess whether ESG connectedness reflects persistent macroeconomic risk factors. By averaging across firm types, we effectively filter out idiosyncratic noise, isolating ESG shocks that are broad-based and relevant to the market as a whole.

Therefore, in this section we assess whether the aggregate ESG connectedness index contains systematic return-predictive information for green and brown firms. This test allows us to examine whether ESG connectedness serves as a market-wide pricing factor, consistent with the interpretation of ESG as a systematic risk premium channel, as proposed in Chu et al. (2020).

Tables C.1 and C.2 report the estimated slope coefficients β_h and corresponding t-statistics from the in-sample predictive regressions of future market excess returns for both green (Table C.1) and brown (Table C.2) firms on ESG connectedness at short- and long-term frequencies respectively.[19]

[19] Returns were annualized and expressed in percentage points (i.e., multiplied by 12 and 100) to facilitate interpretation of the estimated β coefficients. This transformation affects only the scale of the coefficients, shrinking β estimates by a factor of 100, but does not alter R^2, t-statistics, or Wald

[Table C.1 and Table C.2 around here]

In Tables C.1 and C.2 we document a clear frequency gradient in the predictive content of the aggregate ESG connectedness index. The low-frequency (long-term) component delivers strong and persistent return predictability, especially for green firms, consistent with the idea that ESG embeds slow-moving information about fundamentals and risk premia.

Short-frequency connectedness becomes statistically meaningful after only a few months and strengthens with the horizon. For green firms (Table C.1), the short-run slope is significant at the 5% level by 3 months horizon ($t = 2.52$) and highly significant thereafter, with t-statistics exceeding 7 from approximately 13 months onward and peaking at $t = 11.78$ by $h = 24$. Brown firms (Table C.2) display the same profile: short-run coefficients turn significant by the first year and reach $t = 12.32$ at $h = 24$. Given our scaling (annualised returns in percentage points and z-scored predictors), these slopes read as the change in the annualised excess return (in percentage points) associated with a one–standard-deviation increase in ESG connectedness. For example, at $h = 24$ the short-run coefficient implies an increase of roughly 0.021 pp for green firms and 0.007 pp for brown firms, indicating a materially stronger short-frequency response for green firms at long horizons.

Long-frequency ESG connectedness gains importance even more sharply as the horizon extends. For green firms, significance emerges around $h = 13$ ($t = 2.41$) and intensifies monotonically, reaching $t = 17.59$ at $h = 24$. Brown firms follow a parallel path, muted at early horizons (all $t < 2$) but robust beyond $h \approx 13$, with $t = 18.10$ by 24 months horizon. The economic magnitudes are larger on the long-frequency leg and differ across firm types: at 24 months, a one–standard-deviation increase in long-run ESG connectedness is associated with an expected return rise of about 0.465 pp for green firms versus 0.155 pp for brown firms. The green–brown gap therefore widens with the horizon on the long-frequency dimension, consistent with a stronger reputation/intangibles channel for already-green firms.

Taken together, these results suggest that aggregate ESG connectedness captures broad, slowly moving forces, policy momentum, investor reallocation, and reputational spillovers, that accumulate and shape returns over time. This is in line with recent evidence that ESG activities can influence future firm fundamentals and reduce information risk, thereby enhancing return predictability at the aggregate level (Chu et al. (2020)[20]). This suggests that persistent ESG factors, such as reputational effects, struc-

statistics, which are scale-invariant.

[20] Chu et al. (2020) argue that ESG risk exhibits systematic components and that composite ESG indices predict aggregate firm fundamentals, even after controlling for traditional return predictors.

tural industry shifts, or evolving long-term sustainability strategies, exert a measurable influence on short-horizon returns.

Additionally, looking at Table C.1 and C.2 together, the results suggest that, for green firms, ESG-related spillovers are gradually incorporated into asset prices, consistent with the view that ESG performance, often driven by long-term strategic initiatives and policy alignment, requires time to be fully reflected in market valuations. This aligns with literature emphasising that the benefits of ESG integration for green firms manifest progressively over extended periods. Green firms, often seen as already aligned with sustainability, might be less sensitive to short-term fluctuations in ESG factors but show a stronger response to structural, long-term ESG shifts that align with their core values (e.g., corporate sustainability, regulatory change, or green innovation). The lack of significance in the early horizons for long-term ESG connectedness could be interpreted as green firms already operating with strong ESG practices, making them less sensitive to immediate ESG shocks, but more responsive to long-term ESG shifts. This is consistent with the theoretical framework of Pedersen, Fitzgibbons, and Pomorski (2021), who argue that ESG characteristics predict future returns when they correlate with fundamentals rather than investor sentiment.[21]

For both green and brown all the ESG measure of connectedness is positively priced into firms returns, at both short- and long term frequency (Edmans (2011)[22], Pedersen, Fitzgibbons, and Pomorski (2021)). The ESG signal reflects a market consensus, incorporating inter-group spillovers: green firm dynamics (e.g., proactive sustainability strategies or regulatory compliance) may transmit to brown firms through capital reallocation, reputational benchmarking, or sectoral transitions. Consequently, brown firms become more responsive to ESG shocks when the signal integrates green firm influence.

Taken together, the evidence answers our two guiding questions in the affirmative. First, ESG ratings contain a slow-moving component that forecasts long-horizon performance and risk pricing: the long-frequency leg is the dominant predictor at multi-quarter horizons. Second, long-frequency connectedness has stronger predictive power for re-

Their findings suggest that ESG activities are linked to future fundamentals through both cost-increasing and value-enhancing mechanisms.

[21]Pedersen, Fitzgibbons, and Pomorski (2021) provide a theoretical framework where ESG characteristics predict future firm profits and returns when some investors are ESG-unaware. In their model, a positive return premium can emerge through a fundamental channel, when ESG is informative about future cash flows. This long-term effect contrasts with non, fundamental channels like investor preferences, which are more likely to influence prices only in the short run.

[22]This result supports the studies that shows a positive relationship between high ESG metrics and expected returns Edmans (2011). Edmans (2011) shows that stocks with higher employee satisfaction generate positive abnormal returns.

turns than short-frequency connectedness at long horizons, and the strength and timing are type-dependent: effects are larger and arrive earlier for green firms, while brown firms display the same qualitative pattern with modestly later peaks, consistent with transition and compliance frictions. These time-series results align with recent evidence that composite ESG signals predict future fundamentals and reduce information risk at the aggregate level Chu et al. (2020), and with equilibrium views in which ESG characteristics predict returns primarily through a fundamental channel rather than through transitory sentiment Pedersen, Fitzgibbons, and Pomorski (2021). They are also broadly consistent with studies linking higher ESG/CSR quality to subsequent performance and valuation improvements Edmans (2011). Overall, by aggregating across firm types we filter out idiosyncratic reallocations and reveal the systematic ESG component that is priced over long horizons across the green–brown spectrum.

Figures C.5 to C.6 illustrate the predictive power (R^2) of ESG connectedness across short- and long-term frequency bands, using various measures (mean, median, 1% quantile, and 5% quantile) over forecast horizons ranging from 1 to 24 months. Figures C.5 pertain to green firms, while Figures C.6 focus on brown firms. These figures provide critical insights into how different segments of the ESG connectedness distribution relate to return predictability, particularly when accounting for firm-level heterogeneity in ESG responsiveness.

[**Figure C.5 to Figure C.6 around here**]

For green firms (Figure C.5), both the short- and long-term frequency components exhibit substantial predictive power, but their trajectories differ in a way that becomes increasingly pronounced at longer horizons. In panel (a), the median short-term R^2 rises rapidly from the high-20% range at $h = 1$ to roughly 40% by horizons around 4 to 6 months, then remains relatively stable through the mid-horizons. The long-term median, in contrast, increases more steadily and begins to dominate from roughly the 10 to 12 month horizon onward. A clear late-horizon amplification emerges after about $h \approx 17$: both frequencies jump sharply, but the long-term component remains consistently above the short-term series and peaks at very high explanatory power around 22–23 month horizon (approximately 75–80%, versus roughly 65–70% for the short-term component). This pattern indicates that, while short-horizon ESG connectedness contains non-trivial information, the most persistent and economically meaningful predictability for green firms is concentrated in the long-horizon component, consistent with the idea that sustainability strategies and investor demand shifts are incorporated gradually into prices (Pástor, Stambaugh, and Taylor (2021) and Chu et al. (2020)).

Panels (b) and (c), based on the 1% and 5% quantiles, reinforce this interpretation and highlight the role of heterogeneity in ESG responsiveness. At early horizons, tail-based measures already deliver comparatively high R^2 values (typically in the 30–45% range), suggesting that extreme realizations of ESG connectedness contain strong predictive content even in the short run. Through the mid-horizons, the long-term tail measures remain persistently above the short-term ones, and both exhibit a temporary drawdown around approximately 20 months that is followed by a pronounced surge at 22–23 month horizon. In the upper tail (5%), the long-term series reaches its highest values (around the low-to-mid 70% range), while the short-term series also climbs sharply but remains lower (mid-60% range). Overall, the tails behave like an "amplified" version of the median: short-term connectedness captures more transitory, event-driven predictability, whereas long-term connectedness becomes the dominant driver as horizons lengthen, particularly when focusing on extreme ESG connectedness states. The late-horizon acceleration suggests that markets progressively transform episodic ESG shocks into persistent pricing effects, which are most visible once we move beyond average connectedness and examine the full distribution.

For brown firms (Figure C.6), ESG connectedness displays strong and increasingly persistent predictive power as the forecast horizon lengthens, with a clear handover from short- to long-term frequency components. In panel (a) (median), short-term R^2 starts relatively high (around 30%) and increases gradually through the medium horizons, while the long-term component, initially lower, catches up by roughly between 10–12 month horizon and then remains consistently above the short-term series thereafter. From about 17 months onward, both measures experience a pronounced late-horizon acceleration, with the long-term median peaking close to 75–80% around 22 to 23 month horizon, compared with roughly 65–70% for the short-term component, before both ease back slightly by 24 month.

Panels (b) and (c) (1% and 5% quantiles) amplify the previous message: tail-based connectedness measures deliver large explanatory power throughout the horizon range, but the long-term tail signal dominates beyond the mid-horizons and reaches its maximum at 22 to 23 month horizon (around 70% in the 1% tail and close to 80% in the 5% tail). While the short-term tails also rise sharply at long horizons, they remain below the long-term series and exhibit a temporary drawdown around approximately 20 month horizon followed by a rapid rebound.

Overall, the new evidence suggests that for brown firms the predictive content of ESG connectedness is not confined to rare, tail-only episodes: it builds up in the median and becomes economically strongest in the long-term frequency band, consistent with a slow-moving transition-risk channel that increasingly drives coordinated repricing at longer horizons. Taken together with the green-firm results, this reinforces the value of a frequency- and quantile-based lens: short-term connectedness is informative but comparatively transitory, whereas long-term connectedness, especially in the tails, captures the persistent component of ESG-related predictability with direct implications for risk monitoring and horizon-specific portfolio design.

To sharpen the contrast between short- and long-term predictability, we plot, separately for the mean, median, and the 1% and 5% quantiles, the difference in explanatory power, across horizons[23]. These difference-in-R^2 curves provide a compact, scale-free comparison of frequency performance: positive values indicate that short-term connectedness explains more variation at that horizon, while negative values indicate an advantage for long-term connectedness. Sign changes around zero mark horizons where leadership flips, highlighting regime shifts in how ESG information is priced over time.

[**Figure C.7 to Figure C.8 around here**]

For green firms (Figure C.7), the ΔR^2 profiles indicate a systematic shift in predictive dominance from short- to long-term ESG connectedness as horizons lengthen. Short-term components outperform only at early horizons, most clearly in the mean and, more modestly, in the median, while the advantage reverses beyond roughly one year, with long-term connectedness delivering higher explanatory power through the 18–24 month window. This reversal is strongest in the tails: the 1% quantile is long-term dominated across virtually all horizons, and the 5% quantile switches to a persistent long-term advantage from around 9–10 months onward. The evidence suggests that green-firm predictability is primarily driven by slow-moving, long-horizon ESG dynamics, particularly in extreme connectedness states.

For brown firms (Figure C.8), the ΔR_h^2 evidence points to a systematic shift from short-term to long-term ESG connectedness as horizons extend. Short-term connectedness dominates only at early horizons, most clearly in the mean and briefly in the median, whereas long-term connectedness becomes superior from roughly the one-year horizon onward and remains so through 18–24 months. This long-horizon advantage is strongest in the tails: the 1% quantile is long-term dominated almost throughout, and the 5% quantile switches to persistent long-term dominance from around 9–10 months. Thus, predictability for brown firms increasingly reflects slow-moving transition-risk repricing, particularly in extreme connectedness states.

Taken together, the results point to a consistent frequency-based hierarchy in ESG return predictability. For both green and brown firms, short-term connectedness carries

[23]To compare frequencies on a like-for-like basis, we compute ΔR_h^2 ($\Delta R_h^2 \equiv R^2_{\text{Short},h} - R^2_{\text{Long},h}$) for each statistic (Mean, Median, 1%, 5%) and automate the calculation and visualization in MATLAB.

relatively more information at early horizons (particularly in mean/median measures), but predictive leadership rotates toward the long-term component as horizons extend. This transition is most pronounced in the tails, where long-term connectedness dominates across a wide range of horizons and captures the persistent component of ESG-related pricing. Overall, ESG predictability appears primarily long-horizon and distributionally concentrated, consistent with slow-moving adjustment to sustainability fundamentals and delayed transition-risk repricing (Pedersen, Fitzgibbons, and Pomorski (2021), Chu et al. (2020)).

3.5.2 Firm Fundamentals and ESG Connectedness

So far, our compelling evidence shows the differences in predictability of our ESG measure of connectedness when we compare short- with long-term frequency for both green and brown firms. A natural question is whether this predictability simply reflects exposure to business-cycle fundamentals, or whether it also captures slow-moving intangible capital - reputation, trust, and organizational alignment with sustainability.

To probe this, we move beyond excess returns and test the link between frequency-specific ESG connectedness and firm fundamentals constructed from WRDS (Compustat), following the approach in Chu et al. (2020) and related work. The design mirrors the underlying economics: profit-maximizing actions are near-term and cash-flow oriented, whereas reputation formation is gradual and persistent. Accordingly, we examine whether short-frequency connectedness loads more on profit proxies (e.g., margins, asset utilization), while long-frequency connectedness loads more on reputation/intangible proxies, using horizon-by-horizon local projections.

This exercise also addresses the concern, raised by Chu et al. (2020), S. Li (2023), and Pedersen, Fitzgibbons, and Pomorski (2021), that ESG predictability could be an artifact of business-cycle risk. In their markets-to-macro tests, standard aggregate fundamental growth measures do not subsume ESG's forecasting power. We extend that logic at the firm-fundamental level by contrasting profit and reputation channels across frequencies.

In this section, we study whether information in ESG connectedness anticipates changes in fundamentals at the aggregate (market-level) series built from firm panels. For each fundamental, gross profit margin (GPM)[24], return on assets (ROA)[25], return

[24] GPM is gross profit over sales, computed as $(SALE - COGS)/SALE$ using Compustat items; quarterly values are carried forward to months.

[25] ROA is net income over average total assets, $NIQ/\big((ATQ_t + ATQ_{t-1})/2\big)$.

on equity (ROE)[26], and gross profit over total assets (GPTA)[27], we collapse firms to a single monthly series.

The baseline aggregation is the cross-sectional mean (value-weighted aggregates are reported as a robustness check when market-capitalization weights are available). To reduce scale effects and outlier influence before aggregation, firm-level fundamentals are winsorized at the 1st–99th percentiles, and all predictors are standardized.

We run horizon-specific local projections that forecast forward changes in the aggregate fundamental using ESG connectedness at different frequencies. For each forecast horizon $h \in \{1, 3, 6, 12, 24\}$ months, the dependent variable is the forward log change,

$$\Delta \log(1+F)_{t\to t+h} = \log\Big(1+F_{t+h}\Big) - \log\Big(1+F_t\Big),$$

which materially reduces heteroskedasticity for ratios (simple differences yield qualitatively similar conclusions). Here, F_t denotes the aggregate monthly fundamental (GPM, ROA, ROE, or GPTA), t is the month index, and h is the forecast horizon in months. The predictors are the short- and long-frequency ESG connectedness indices, ESG_t^S and ESG_t^L, obtained from the spectral decomposition described earlier (standardized to zero mean and unit variance). To isolate the information in each frequency, we estimate separate predictive regressions:

$$\Delta \log(1+F)_{t\to t+h} = \alpha_h + \beta_h^{(S)}\,\mathrm{ESG}_t^S + \varepsilon_{t+h}, \qquad \Delta \log(1+F)_{t\to t+h} = \alpha_h + \beta_h^{(L)}\,\mathrm{ESG}_t^L + \varepsilon_{t+h},$$

where α_h is a horizon-specific intercept, $\beta_h^{(S)}$ and $\beta_h^{(L)}$ are the slopes (interpreted per 1σ change in the respective ESG index), and ε_{t+h} is the forecast error.

Because targets use overlapping future months, we compute Newey–West heteroskedasticity- and autocorrelation-robust standard errors with lag length $\max\{7, h-1\}$, standard for overlapping-window forecasts. These choices, log-changes for the dependent variable, overlap, aware HAC lags, winsorization before aggregation, and z-scoring of predictors, tighten inference and yield notably sharper t-statistics than raw-difference specifications.

This section tests whether frequency-specific ESG information leads fundamentals over different horizons. A positive and statistically significant $\beta_h^{(S)}$ at short horizons indicates that higher short-run connectedness is followed by near-term improvements in profitability measures (a cash-flow/operations channel). Conversely, a $\beta_h^{(L)}$ that strengthens with horizon supports the view that long-run connectedness captures slow-

[26] ROE is net income over average common shareholders' equity, $NIQ/\big((SEQ_t + SEQ_{t-1})/2\big)$.

[27] GPTA follows Novy–Marx (2013): gross profits over average total assets, $(SALE - COGS)/\big((ATQ_t + ATQ_{t-1})/2\big)$.

moving intangible capital—reputation, trust, and organizational alignment—whose effects materialize gradually in accounting outcomes. We visualize these dynamics by plotting the coefficient paths β_h with 90% Newey–West confidence bands for short and long components on the same axes and, in a companion panel, the corresponding $R^2(h)$ profiles.

Implementation is deliberately light-touch to preserve comparability with our return-predictability tests: we retain the same sample trimming and time index used for ESG connectedness (rolling-window length k and step size), align all series at the monthly frequency, and keep the baseline specification parsimonious to isolate the information content of each ESG frequency. This design yields a clear, model-light map from short-versus long-horizon ESG signals to subsequent changes in fundamentals and complements the green–versus–brown splits reported in the main results. Tables C.3 (Panel A and B) and C.4 (Panel C and D) below summarize the estimated relations for green and brown firms, respectively.

[Table C.3 and Table C.4 around here]

[Figure C.9 to Figure C.10 around here]

In the case of green firms (Table C.3), frequency-specific ESG connectedness predicts forward changes in profitability with a systematic horizon profile, and the long-frequency component plays the dominant role. For ROA and GPTA (Panel A), short-frequency coefficients are modestly positive at very short horizons and become economically and statistically meaningful only at longer horizons (from approximately $h \approx 19$ onward). By contrast, long-frequency coefficients exhibit the same qualitative U-shaped pattern but with larger magnitudes and tighter inference: small positives at $h = 1$–3, a pronounced mid-horizon dip, and a strong, sustained increase from roughly $h \approx 19$ through $h = 24$. Because predictors are standardized, a one–standard-deviation (1σ) increase in long-run connectedness is associated with substantially larger gains in $\Delta \log(1 + \text{ROA})$ and $\Delta \log(1 + \text{GPTA})$ than an equivalent increase in the short-run measure, particularly beyond approximately one-and-a-half years.

For gross profit margin (GPM) in Panel B (Table C.3), the short-frequency component is close to zero and statistically weak up to about $h \leq 16$, and only then turns significantly positive. The long-frequency component is mildly negative over the first year, consistent with adjustment and transition costs, but becomes strongly positive from about $h \approx 18$ onward, again with larger peak magnitudes and higher explanatory power than the short-frequency specification.

In contrast, ROE (Panel B) loads negatively on ESG connectedness, especially at the long frequency. Short-frequency coefficients are significantly negative over intermediate and long horizons, whereas long-frequency coefficients are negative from early horizons and become most pronounced around $h \approx 20$–22, where model fit also peaks. This pattern is consistent with green firms financing sustained ESG and intangible investments by retaining earnings, issuing equity, and deleveraging, thereby expanding the book-equity base faster than net income within the measurement window.

Overall, Table C.3 (Panels A–B) indicates that: (i) both ESG frequencies carry predictive content for green-firm profitability; (ii) long-frequency (reputation/intangibles) connectedness dominates at medium-to-long horizons for profitability and margins; and (iii) the short-frequency (operations/cash-flow) channel becomes economically relevant once implementation lags are absorbed.

For brown firms (Table C.4, Panel C), frequency-specific ESG connectedness predicts forward changes in ROA only at relatively long horizons. Short-frequency coefficients become economically and statistically meaningful only at the very back end, with large and precisely estimated effects around 21-23 horizon (with $|t| \approx 3$–4) and borderline significance at $h = 24$. This delayed response is consistent with ESG activity operating primarily through cash-flow and operational channels (process re-engineering, compliance routines, cost management) that require multiple reporting cycles to be reflected in accounting profitability. Long-frequency coefficients also strengthen at long horizons (with $|t| \approx 2.4$–3.8 at $h = 22$–24), but exhibit a temporary negative blip at a horizon equal to 20 (t-statistic around -2.6), plausibly reflecting transition costs or cyclical sensitivity before intangible gains materialize. Given standardized predictors, a 1σ increase in long-run connectedness is associated with substantial increases in $\Delta \log(1 + \mathrm{ROA})$ at the outer horizons, although the profile is less smooth than for green firms.

Profitability relative to the asset base (GPTA) in Table C.4 (Panel C) exhibits clear horizon-dependent predictability. Short-frequency effects are small at short horizons, become significant around 13–16 horizon, and are very strong around 21–23, before easing at $h = 24$. Long-frequency effects surface in the mid-teens, briefly turn negative at $h = 20$, and then re-emerge strongly at $h = 21$–23. This pattern is consistent with operational and cost-efficiency gains (short frequency) needing time to compress costs relative to assets, while reputation, stakeholder relationships, and supply-chain/customer alignment (long frequency) accumulate more gradually and pay off over the medium to long run.

Looking at gross profit margin (GPM) in Table C.4 (Panel D) sharpens the frequency contrast. The short-frequency signal is modest at very short horizons but becomes economically and statistically relevant from the mid-teens onward, with clear significance around $h = 15$ and strong effects over $h = 20$–24. The long-frequency signal turns positive and precise earlier in the medium run (already by $h = 4$–5), reappears around $h = 14$–16, and is very strong at $h = 20$–24. Both frequencies display a mild dip around 8–11 horizon, consistent with temporary adjustment costs, followed by a sharp rebound. Overall, GPM results support the two-channel view: near-term operational actions (short frequency) take time to pass through to margins, while slow-moving intangibles (long frequency) contribute earlier in the medium run and dominate at long horizons.

Lastly, returns on equity (ROE) (Table C.4, Panel D) display a U-shaped response. Short-frequency coefficients are small and mostly negative in year one, significantly negative around $h = 17$–19, and then flip positive and significant at $h = 22$–24, consistent with near-term transition costs (capital expenditure, compliance, equity issuance) that depress net income relative to book equity before operational benefits dominate. The long-frequency component is even more pronounced: muted at very short horizons, significantly negative over $h = 17$–21, followed by a strong positive reversal at $h = 22$–24. With standardized predictors, a 1σ increase in long-run connectedness initially coincides with balance-sheet adjustments that expand the equity base faster than earnings (pressuring ROE) but eventually pays off at the outer horizons as both operational gains and accumulated intangible capital dominate.The ROE profiles reconcile with the profitability results: as firms invest in ESG and intangible capital and adjust their capital structure, equity-based returns dip in the medium run before improving at the longest horizons.

Taken together, Panels C–D (Table C.4) show that brown-firm evidence is consistent with the paper's two-channel hypothesis. Short-frequency of the ESG connectedness measure (operations/cash-flow) maps into profitability only after several reporting cycles, with the sharpest gains emerging at late horizons for ROA, GPM, and GPTA. Long-frequency connectedness generates earlier medium-run signals and robust long-horizon payoffs, albeit with occasional mid-horizon negatives that likely reflect transition and adjustment costs.

Lastly, comparing Tables C.3 and C.4 reveals a common frequency split but different timing and intensity across firm types. For green firms, long-frequency connectedness (reputation/intangibles) dominates profitability at medium–to–long horizons: after a mid-horizon dip, ROA and GPTA coefficients rise steeply from $h \approx 19$ to 24 with larger magnitudes than their short-frequency counterparts, while GPM turns strongly positive only in the late teens and ROE remains predominantly negative—consistent with equity-financed transitions and deleveraging diluting returns on equity even as asset- and margin-based profitability improves. Brown firms display the same qualitative separation of channels but with a more pronounced transition window and later payoffs:

short-frequency slopes for ROA, GPM, and GPTA become strongly positive only after several reporting cycles, peaking at the longest horizons, whereas long-frequency effects emerge earlier in the medium run and then surge at $h = 20$–24 after a mid-horizon trough.

In addition, looking at Figure C.9 (green firms) the predictive $R^2(h)$ profiles in Panel A indicate that ESG connectedness explains green-firm fundamentals primarily at long horizons. For both ROA (Figure C.9a) and GPTA (Figure C.9b), fit is modest at short horizons and remains subdued through mid horizons, but rises sharply from about approximately 15–16 months horizon and strengthens further beyond $h \approx 20$. In these two profitability measures, the long-frequency component consistently delivers the larger share of explanatory power, pointing to a slow-moving mechanism through which ESG-linked systematic risk translates into balance-sheet and operating performance over time.

Panel B confirms that this pattern extends to alternative accounting outcomes, albeit with different magnitudes. For GPM (Figure C.9c), predictability is concentrated in a narrower window at longer horizons, where $R^2(h)$ increases materially and the long-run component dominates the short-run one. ROE (Figure C.9d) displays a similarly horizon-dependent profile, with limited explanatory power over most short and medium horizons but a pronounced increase at longer horizons. Overall, across Panels A and B, the $R^2(h)$ evidence suggests that for green firms the informational content of ESG connectedness is chiefly long-run, consistent with gradual adjustment in fundamentals (e.g., reputation, stakeholder trust, and organizational alignment) rather than a near-term cash-flow channel.

For brown firms (Figure C.10) the predictive $R^2(h)$ profiles in Panel A suggest a more episodic and horizon-dependent link between ESG connectedness and asset-based profitability for brown firms than for green firms. For ROA (Figure C.10a) and GPTA (Figure C.10b), explanatory power is generally small at short horizons, with an early long-run advantage more visible for GPTA, but the main predictability emerges at intermediate horizons: both measures display a pronounced hump around 13 to 16 months horizon, where $R^2(h)$ rises materially and the long-frequency component typically matches or slightly exceeds the short-frequency component. After a sharp decline around $h \approx 17$–19, a second predictability pocket appears at longer horizons ($h \approx 21$–23), again with the long-run component often leading, consistent with a slower-moving fundamental adjustment channel that operates intermittently rather than monotonically with the horizon.

Panel B (Figure C.10) highlights stronger heterogeneity across accounting outcomes and a clearer role for short-run dynamics in margins. For GPM (Figure C.10c), predictability is concentrated in discrete windows, culminating in a sharp spike around $h \approx 20$ months where the short-run component dominates, consistent with a near-term operating/cash-flow channel in which transitory ESG-linked shocks are followed by margin adjustments. By contrast, ROE (Figure C.10d) exhibits limited explanatory power across most short and medium horizons, but displays pronounced increases at longer horizons (notably around $h \approx 18$ and again towards $h \approx 24$), where the long-frequency component becomes dominant. Overall, across Panels A and B, brown-firm fundamentals appear to be led by ESG connectedness through a combination of mid-horizon and late-horizon effects, with the short-run component mattering most for margin dynamics and the long-run component becoming more informative for equity-based profitability at longer horizons.

Overall, the evidence points to a clear asymmetry in the fundamental channel. Green firms display earlier and more persistent gains driven by the long-frequency component, consistent with gradual accumulation of intangible capital and sustained stakeholder alignment. Brown firms, in contrast, exhibit a more delayed response, with economically meaningful improvements emerging only at longer horizons as operational reallocation, compliance investment, and slow-moving intangibles are progressively reflected in accounting outcomes. The divergence is particularly visible in the ROE responses: green firms' ROE effects are comparatively weak and often negative over much of the horizon, whereas brown firms show a pronounced U-shaped pattern with a late-horizon reversal, highlighting distinct financing constraints and balance-sheet adjustments during the transition.

3.5.3 Economic Explanations

In the previous sections we explore the economic mechanisms underlying the return predictability of ESG connectedness, particularly the contrasting dynamics across short- and long-horizon frequencies and between green and brown firms. A central question emerges: what drives the predictive power of ESG signals? Our interpretation is that ESG connectedness captures the extent to which ESG-related information becomes common across firms and is transmitted through return co-movement. In that sense, it differs from raw ESG levels, which primarily describe a firm's own standing at a point in time. It also differs from broad slow-moving macroeconomic trends. While macro forces such as the business cycle, inflation expectations, energy prices, or aggregate policy uncertainty may themselves evolve gradually, ESG connectedness measures how ESG-related shocks propagate across firms conditional on heterogeneous exposure, business models, and market reassessment. The object of interest is therefore not persistence per se, but the extent to which ESG information generates systematic cross-sectional dependence that is subsequently reflected in both prices and fundamentals.

A growing body of literature suggests that ESG influences firm value through multiple channels, including expected cash flows, discount rates, and investor preferences. A foundational theoretical contribution by Pedersen, Fitzgibbons, and Pomorski (2021)[28] introduces the concept of the ESG-efficient frontier, which formalises the trade-off between investors' financial return objectives and their non-pecuniary preferences for sustainability. In their equilibrium asset-pricing model, ESG characteristics affect prices both by altering expected cash flows, through improved operating performance, stakeholder relationships, supply-chain resilience, and regulatory positioning, and by lowering the discount rate applied by ESG-conscious investors. This reduction in the cost of capital can relax financing constraints, support investment, and reinforce long-run growth. These mechanisms map naturally into our results: for green firms, the predictive power of ESG connectedness is muted at short horizons but becomes statistically significant and economically meaningful at longer horizons, especially after around 13 months.[29] This pattern is consistent with a gradual incorporation of ESG-

[28]Pedersen, Fitzgibbons, and Pomorski (2021) develop a theoretical model in which investors who anticipate future profitability from ESG improvements, prior to full market incorporation, can earn higher returns on green assets. In contrast, Pástor, Stambaugh, and Taylor (2021) assumes market efficiency, whereby differences in expected future profits are immediately reflected in asset prices. However, Pástor, Stambaugh, and Taylor (2022) provides empirical evidence that prices adjust gradually to ESG-related information, implying a deviation from the strong-form efficiency assumed in earlier models.

[29]Edmans (2011) argues that intangible corporate information, such as ESG performance, is often underappreciated in the short run. This delayed price adjustment is consistent with behavioural explanations that challenge the efficient-market benchmark in Pástor, Stambaugh, and Taylor (2021).

related fundamentals into equity prices, where the benefits of sustainable practices materialise only over time as firms build reputational capital, strengthen stakeholder relationships, improve operating efficiency, and adapt their business models to transition-related pressures.

Using aggregate ESG connectedness as a market-wide measure of systematic ESG risk, brown firms exhibit clear and persistent return predictability that also strengthens with the forecast horizon. Economically, the long-frequency slopes are larger than the short-frequency slopes across horizons, in annualised percentage points per one-standard-deviation increase in connectedness, indicating that slow-moving ESG linkages dominate the long-horizon pricing of brown firms. However, these long-frequency dynamics should not be interpreted as mere exposure to a generic macro trend. Rather, they reflect the gradual repricing of firms whose cash flows and balance sheets are especially sensitive to transition-related channels such as regulatory tightening, carbon-intensive production, stranded-asset risk, supply-chain adaptation, and reputational spillovers. In brown firms, ESG connectedness becomes powerful precisely because these exposures are uneven across firms but increasingly recognised by the market over time. The monotonic rise in statistical power with h and the absence of mid-horizon reversals therefore suggest gradual information absorption and capital reallocation rather than transitory overreaction.

Chu et al. (2020) offers a complementary explanation grounded in both behavioural and rational finance. From a behavioural perspective, the market may under-react to ESG information, particularly when its implications for firm value are complex, long-term, or difficult to quantify. This under-reaction is likely to be stronger when a substantial fraction of market participants are ESG-unaware, or when ESG metrics are difficult to compare across firms and providers. Over time, as ESG-aware investors gain influence or as more credible information becomes available, prices adjust, generating return predictability at longer horizons.[30] Chu et al. (2020) also note that ESG activities can initially raise costs, for example through compliance investment, cleaner technologies, supplier screening, workforce policies, or stakeholder initiatives. Yet these same activities can strengthen intangible capital, reduce future frictions with regulators, employees, and communities, and improve long-run profitability. This logic helps explain why ESG connectedness becomes informative at different timescales for green and brown firms in

Market-wide under-reaction to ESG signals implies that investors may initially underweight ESG-related fundamentals, leading to stronger predictability over longer horizons.

[30] Amel-Zadeh and Serafeim (2018) report that many investment professionals either disregard ESG information entirely or use it only qualitatively, often citing the lack of standardised, comparable, and reliable ESG metrics as a key limitation.

our sample: it is not simply that markets respond to ESG labels, but that they gradually price the firm-level consequences of ESG-related adjustment.

Additional frictions help account for the delayed pricing of ESG signals. As noted by Avramov, Cheng, et al. (2022), disagreement across ESG ratings and the absence of standardised disclosure norms introduce noise and uncertainty into ESG assessments, limiting their immediate usefulness for valuation. Investors may be reluctant to act on ESG signals when it is unclear whether a high rating reflects genuine sustainability performance or marketing-driven greenwashing. Recent studies by Gibson Brandon, Krueger, and Schmidt (2021), Duchin, J. Gao, and Xu (2025), and Heath et al. (2023) document the rise of such practices, which can undermine the credibility of ESG metrics and reduce market efficiency. This informational friction delays the incorporation of ESG considerations into prices, particularly for green firms whose ESG strategies are long-term and less easily summarised by headline ratings. In this setting, ESG connectedness is economically useful because it places less weight on the level of any single score and more weight on the degree to which ESG-related information is common, persistent, and transmitted across firms.

Importantly, recent evidence suggests that credible ESG strategies can reduce downside risk and enhance long-term firm value through reputational and operational channels. Hoepner et al. (2024)[31] argue that ESG engagement, when aligned with material issues and risk-mitigation strategies, improves corporate resilience and reduces volatility. This supports our finding that ESG connectedness becomes particularly predictive at longer horizons for green firms. Market participants may take time to appreciate the strategic value of ESG, especially when the benefits are non-linear, contingent on policy evolution, or tied to intangible capabilities such as organisational learning, customer trust, and stakeholder cooperation.

A key innovation in our empirical approach is the disaggregation of green and brown firms, which allows us to uncover patterns that are obscured in aggregate analyses. Previous studies often pool firms regardless of ESG orientation, masking heterogeneity in how firms respond to ESG-related forces. Chu et al. (2020) caution against such aggregation, arguing that it can dilute or even reverse observed return effects, especially when ESG preferences are concentrated among a subset of investors. By separating green and brown firms, we capture asymmetric responses to ESG connectedness: green firms display persistent but delayed return effects, while brown firms exhibit earlier and stronger sensitivity to systematic ESG repricing. Our frequency-domain approach

[31] Hoepner et al. (2024) further show that ESG engagement, particularly through active ownership, can reduce downside risks and enhance long-term firm value, providing another channel through which ESG considerations can generate financial benefits for shareholders.

further shows that these dynamics unfold over distinct timescales, with long-frequency connectedness linked to structural valuation effects and short-frequency connectedness reflecting more immediate revisions in expectations, implementation costs, and reactive repositioning.

Our frequency-domain results support two distinct but related mechanisms through which ESG enters both fundamentals and prices. The short-frequency ESG connectedness measure captures actions relatively proximate to cash flows, such as process re-engineering, input efficiency, supplier screening, compliance routines, and operational adaptation. These mechanisms are firm-level in origin, but connectedness becomes relevant when such actions are undertaken across related firms facing similar ESG pressures or investor scrutiny. Because implementation takes time, these effects should appear first in operating fundamentals such as gross profit margin (GPM) and gross profit-to-assets (GPTA), and only later in broader profitability measures such as return on assets (ROA). By contrast, long-frequency connectedness behaves more like slow-moving intangible capital: reputation, stakeholder trust, customer loyalty, supply-chain reliability, internal organisational alignment, and strategic preparedness for transition-related change. These channels accumulate gradually and therefore produce larger and more persistent effects at multi-year horizons.

This tighter link with fundamentals is central to our interpretation. If ESG connectedness were simply proxying for a broad macro trend, one would expect a more diffuse relationship with returns and weaker evidence that it maps into firm-level operating outcomes. Instead, the evidence is more consistent with a transmission mechanism that works through firms' underlying economics. Short-frequency connectedness predicts later improvements in operating performance after implementation lags, while long-frequency connectedness is associated with persistent gains in profitability metrics that are naturally linked to durable changes in business quality, financing conditions, and intangible capital. The fact that these patterns differ across green and brown firms further indicates that connectedness is capturing heterogeneous firm exposure and adjustment, not merely aggregate drift.

The timing and intensity of these channels differ across firm types. For green firms, long-frequency effects dominate in both magnitude and precision at medium- to long-horizons: ROA and GPTA exhibit a mid-horizon dip followed by strong and sustained increases from roughly $h \approx 19$ to 24, while GPM turns significantly positive from the high teens onward. Over the same horizons, short-frequency effects become economically relevant but remain smaller than their long-frequency counterparts. In contrast, green-firm ROE loads negatively, especially on the long-frequency leg, consistent with equity-financed investment and deleveraging that expand the book-equity base faster than earnings within our window, even as ROA and GPTA rise. Economically, this suggests that green firms convert ESG-related positioning into fundamentals chiefly through persistent improvements in operating quality and intangible capital, rather than through immediate shareholder payouts.

For brown firms, the qualitative split is similar, but the payoffs are later and more uneven. Fundamentals display transitional headwinds in the mid-teens, followed by pronounced late-horizon gains for ROA, GPM, and GPTA on both frequency legs, with long-frequency effects strengthening most at the back end. ROE exhibits a U-shape: significantly negative in the mid-teens, consistent with adjustment costs, compliance spending, financing frictions, and balance-sheet reshaping, before reversing to positive and significant only at the longest horizons once operational improvements and accumulated intangibles materialise. This pattern is particularly informative for distinguishing ESG connectedness from macro persistence. What is being priced is not a generic long cycle, but the gradual effect of ESG-related transition pressure on firms whose technologies, assets, and operating models are more exposed to sustainability reallocation. Brown firms appear to absorb these pressures first as cost and restructuring effects, and only later as improved profitability once the adjustment process is more complete.

These mechanisms align closely with the literature. Chu et al. (2020) argue that ESG activity can both raise costs in the short run and build intangible value that improves future fundamentals; at the aggregate level, their composite ESG index predicts future fundamentals, and ESG's forecasting power is not subsumed by standard business-cycle controls. Our results echo this argument, while sharpening it: once ESG information is decomposed by frequency and interpreted through connectedness rather than raw levels, short-run signals align with near- to medium-term operating gains, whereas long-run signals align with persistent improvements in profitability metrics, especially for green firms. Pedersen, Fitzgibbons, and Pomorski (2021) further emphasise that for ESG to generate abnormal returns it must correlate with future fundamentals, and that this fundamental channel is long-lived, whereas demand-based channels are shorter-lived. Our frequency decomposition provides exactly this linkage: the long-frequency component, which we interpret as a proxy for slow-moving intangible and transition-related capital, explains durable multi-year improvement in fundamentals, while the short-frequency component captures operational adjustments that require implementation time but then contribute meaningfully to performance.

Taken together, our results align with, and extend, the literature by showing that

ESG influences market outcomes through informational, operational, reputational, and financial channels, and that these channels are frequency-specific rather than monolithic. The frequency-domain evidence separates relatively near-term operating adjustment from slower-moving intangible and transition channels: short-frequency ESG connectedness predicts near- to medium-term operating improvements after implementation lags, whereas long-frequency connectedness delivers strong and persistent multi-year gains, most pronounced for green firms. This variation in return and fundamentals predictability by firm type and horizon underscores the need to model ESG as a dynamic and heterogeneous force in asset pricing. More importantly, it shows that ESG connectedness should be understood not as a relabelled macro trend, but as a measure of how ESG-related information becomes systematic through cross-firm transmission and is ultimately anchored in firm fundamentals.

3.6 Robustness Checks

3.6.1 IVX-Based Wald Inference

In this section, we revisit the in-sample return predictability analysis using our individual measure of ESG connectedness, applied separately to the excess returns of green and brown firms respectively. As in the main analysis, we distinguish between short-term and long-term ESG connectedness based on frequency-domain decomposition. However, instead of relying solely on Newey–West adjusted t-statistics to assess the statistical significance of the slope coefficients, we adopt the Instrumental Variable with eXtrapolation (IVX) approach introduced by Kostakis, Magdalinos, and Stamatogiannis (2015).

Specifically, we implement the IVX-based Wald test to provide robust inference in the presence of persistent and potentially endogenous predictors, a common concern in predictive regressions involving macro-financial variables and latent ESG factors. The Wald statistic under this approach follows a chi-squared distribution under the null hypothesis of no predictability, enabling reliable and interpretable p-values[32].

To summarize the procedure, we re-estimate the predictive regressions using the IVX framework. The slope coefficients (β) and R^2 values remain identical to those reported in the main analysis, ensuring consistency in model estimates. We replace Newey–West t-statistics with Wald statistics and their associated p-values, derived from the IVX methodology. The updated regression results, reported in Tables C.5 and C.6, allow us to assess the robustness of ESG connectedness as a predictor of excess returns across firm types, accounting for statistical concerns related to persistence and endogeneity.

[**Table C.5 and Table C.6 around here**]

The IVX-based Wald inference presented in Tables C.5 and C.6 confirms the robustness of our main in-sample predictability results, even after accounting for persistence and endogeneity in the ESG connectedness predictors. This alternative inferential framework strengthens the credibility of our findings, as it mitigates concerns associated with traditional t-statistic inference under near-unit-root processes, a frequent issue in macro-financial time series and ESG-related variables.

For green firms, the IVX-adjusted Wald statistics for short-term ESG connectedness become statistically significant at the 5% level from $h = 17$ onward and remain so through $h = 23$ (e.g., $h = 17$: $W = 4.9601$, $p = 0.0259$; $h = 20$: $W = 6.1284$, $p = 0.0133$; $h = 23$:

[32] The IVX Wald test provides valid asymptotic inference even when predictors exhibit near-unit-root behaviour or are endogenous. See Kostakis, Magdalinos, and Stamatogiannis (2015) for theoretical details.

$W = 5.5321$, $p = 0.0187$), with borderline 10% significance at $h = 24$ ($W = 3.6392$, $p = 0.0564$). The long-term component shows weaker and intermittent evidence at short and mid horizons (notably a 5% signal at $h = 1$: $W = 4.0521$, $p = 0.0441$), but turns decisively significant from $h = 17$ onward with rapidly rising test power (e.g., $h = 18$: $W = 9.0315$, $p = 0.0027$; $h = 21$: $W = 13.6420$, $p = 0.0002$; $h = 24$: $W = 8.2956$, $p = 0.0040$). Taken together, these results indicate that short-frequency ESG shocks for green firms accumulate into return-relevant information after several reporting cycles, while the long-frequency (slow-moving) ESG connectedness dominates at medium–long horizons, consistent with the gradual pricing of transition dynamics and structural ESG trends.

In contrast, brown firms display earlier and broader ESG return predictability under IVX inference, especially on the long-frequency leg. Long-term connectedness is already significant at very short horizons (e.g., $h = 1$: $W = 4.2168$, $p = 0.0400$; $h = 2$: $W = 3.9166$, $p = 0.0478$), experiences a short lull around $h = 7$–12, and then turns decisively significant from $h = 13$ onward, tightening rapidly to strong evidence by the outer horizons (e.g., $h = 18$: $W = 11.2489$, $p = 0.0008$; $h = 22$: $W = 16.8335$, $p < 0.0001$; $h = 24$: $W = 9.3202$, $p = 0.0023$). Short-frequency connectedness accumulates more gradually: evidence is marginal at $h = 1$ ($W = 2.7295$, $p = 0.0985$), becomes steadily stronger through the teens, and is uniformly significant from $h = 13$ onward (e.g., $h = 13$: $W = 5.3037$, $p = 0.0213$; $h = 17$: $W = 13.1114$, $p = 0.0003$; $h = 24$: $W = 11.5280$, $p = 0.0007$). This pattern suggests that brown firms, more exposed to regulatory scrutiny, compliance costs, and transition risk, begin to price ESG information both via slow-moving, market-wide signals (long frequency, early and then strongly at long horizons) and via operational adjustments that take several reporting cycles to crystallize.

Importantly, while the magnitude and timing of statistically significant coefficients differ between green and brown firms, the IVX-Wald results reinforce our earlier conclusion: both firm types exhibit return predictability driven by ESG connectedness, particularly at longer horizons, but with differences in intensity and sensitivity depending on firm type. These findings further underscore the necessity of modelling ESG exposure as both persistent and heterogeneous across firm types, and justify the use of robust inference methods in ESG return predictability settings.

3.6.2 Sector-Level Insights into ESG Return Predictability

In this subsection, we conduct a sector-level decomposition of the predictive ESG betas by aggregating firm-level beta coefficients across industrial sectors[33]. The analysis is based on firm-specific predictive regressions where ESG connectedness measures serve as the main explanatory variable. The significant betas are then grouped by sector to investigate whether there are systematic differences in the predictive power of ESG connectedness across industries. This decomposition enables a clearer understanding of how ESG information is priced heterogeneously across sectors. To visually explore the distributional characteristics of sector-level effects, we present boxplots of the filtered beta estimates by sector and across different frequencies. This approach highlights both the central tendency and dispersion of ESG return predictability within and across industries, and allows us to assess sector-specific sensitivity to ESG-related signals.

Specifically, for each firm i, we run predictive regressions of future excess returns on our ESG connectedness measure. The regression model is defined as follows:

$$\bar{r}_{i,t:t+h-1} = \alpha + \beta_{i,h} \cdot \mathrm{ESG}_t + \varepsilon_{t+h}, \tag{3.8}$$

Where $\bar{r}_{i,t:t+h-1}$ denotes the average excess return of firm i over the h-month horizon starting at time t, ESG_t is the ESG connectedness predictor (at a given frequency band), and $\beta_{i,h}$ captures the firm-specific sensitivity to ESG information at forecast horizon h.

The estimation proceeds by first looping through firms within each sector. For each firm i, we estimate the predictive coefficient $\beta_{i,h}$ from equation (3.8) over forecast horizons $h \in \{1, \ldots, 12\}$. The estimated betas $\beta_{i,h}$ are then collected and grouped according to the sectoral classification of each firm. To ensure robustness, we apply a statistical significance filter, retaining only those beta coefficients whose absolute t-statistics exceed the critical value of 1.65, corresponding to a 10% significance level. This procedure enables us to isolate the most meaningful firm-level ESG sensitivities while controlling for estimation noise.

By grouping significant $\beta_{i,h}$ coefficients by sector and plotting their distributions via boxplots, we gain insight into how ESG information differentially influences return predictability across industries. This approach highlights sector-specific dynamics in ESG pricing and allows for the identification of any asymmetries between green and

[33] The industrial sectors represented in our sample are classified based on firms' environmental alignment. Brown firms primarily belong to the industrials and energy sectors, reflecting high carbon intensity and ESG risk exposure. In contrast, green firms are drawn from a more diverse set of sectors, including communication services, utilities, energy, real estate, financials, information technology, and consumer discretionary, which are typically associated with lower environmental impact or proactive ESG practices.

brown firms in response to ESG-related signals and the results are represented bellow.

[**Figure C.11 to Figure C.12 around here**]

Figures C.11 (panel (a) and (b)) represents the boxplot for green firms in our sample aggregated statistically significant betas by sector, assuming that the forecasting horizon is 12 months[34], and across different frequencies, short- and long-term frequencies, respectively. The results offer important insights into the heterogeneity of ESG-related return dynamics across both sectors and time horizons.

Figure C.11 panel (a) (short-frequency ESG connectedness) shows that most green sectors exhibit narrow interquartile ranges with medians close to zero, indicating limited and selective short-horizon predictability. A few industries display modest dispersion or non-zero centres—most notably Industrials and Real Estate, with Utilities and Information Technology showing mild right tails—consistent with event-driven or idiosyncratic reactions (e.g., disclosures, earnings guidance, or regulatory headlines). By contrast, Financials, Health Care, and parts of Communication Services cluster tightly around zero, suggesting that short-frequency ESG shocks are transitory and not broadly priced among green firms.

Figure C.11 panel (b) (long-frequency ESG connectedness) reveals a markedly different pattern: interquartile ranges widen across most sectors and several medians shift away from zero. Industrials, Utilities, Real Estate, and Information Technology display clearly positive medians with substantial dispersion, consistent with slow-moving ESG channels - reputation, stakeholder alignment, and supply-chain resilience, being incorporated more systematically at longer horizons. Consumer Discretionary exhibits the largest spread and a slightly negative centre, pointing to heterogeneous business-model exposure to long-run ESG pressures even within the green cohort. Sectors with sparse coverage (Energy and Health Care) show isolated observations that skew negative, underscoring heterogeneity and potential sample-thickness effects. Overall, Panels (a)–(b) indicate that long-frequency connectedness captures persistent, sector-dependent variation in return predictability for green firms, whereas short-frequency signals remain patchier and more event-driven.

Figure C.12 (panel (a) and (b)), represent boxplots of statistically significant firm-level beta coefficients for the brown firms in our sample, aggregated by sector. Each figure corresponds to a forecasting horizon of 12 months and captures the estimated

[34]A 12-month forecasting horizon was selected as a representative annual period commonly used in asset pricing and risk forecasting. This horizon balances the need to capture meaningful return dynamics while avoiding excessive noise that may arise in shorter-term intervals. It also aligns with standard investment horizons in both academic studies and industry practice, enabling clearer interpretation of ESG-connectedness impacts across temporal frequencies.

ESG connectedness effects across short-, and long-term frequency bands, respectively.

In Figure C.12 (panel (a)), the short-term frequency band reveals clear sectoral differences across brown firms. The industrials sector is centred slightly above zero, with a relatively compact interquartile range, suggesting that short-horizon ESG signals translate into only modest (and fairly stable) return predictability for the typical firm. At the same time, the presence of several large outliers on both sides indicates that a subset of industrial firms reacts much more strongly to ESG news, consistent with heterogeneous exposure to ESG controversies, supply-chain disruptions, or firm-specific short-term repositioning. By contrast, communication services display a more negative median and a wider, negatively skewed distribution, with a longer lower tail. This pattern points to a stronger downside sensitivity to ESG signals at short horizons in this sector, and to more uneven pricing of ESG-related information across firms.

In Figure C.12 (panel (b)), the long-term frequency band amplifies these sectoral contrasts. Industrials remain clustered close to zero (with a slightly positive central tendency), implying limited long-horizon predictability for the median firm, but the very large positive outliers suggest that a small group of industrial firms benefits disproportionately from longer-run ESG dynamics, potentially those with clearer transition trajectories or sustained improvements in ESG fundamentals. In communication services, the distribution shifts further into negative territory and remains comparatively dispersed, indicating that long-horizon ESG signals are priced more persistently and adversely for many firms in this sector. Overall, the long-term evidence suggests a sharper penalty (and greater heterogeneity) in communication services, while industrials exhibit mostly muted effects with occasional pronounced positive predictability for a subset of firms.

Taken together, the sector-level boxplots for both brown and green samples point to a pronounced sectoral asymmetry, and substantial within-sector heterogeneity, in how ESG connectedness maps into return predictability. In the brown universe, the strongest and most persistent pattern remains concentrated in high-carbon sectors, most notably energy, where ESG betas are shifted into negative territory and become more persistent in the long-term band (Ilhan, Sautner, and Vilkov (2021)[35]). By contrast, brown industrials are centred closer to zero, but with notable outliers of both signs, suggesting that ESG signals are not priced uniformly across firms and that any positive

[35]These findings are consistent with Ilhan, Sautner, and Vilkov (2021), who show that high-carbon firms, especially in energy and utilities, face significantly greater downside (tail) risk exposure, particularly over longer horizons. Their evidence implies that markets penalise these firms for transition-related risks, aligning with the negative and more persistent long-horizon ESG betas observed for brown sectors in our analysis.

ESG return premia are concentrated among a subset of transition-ready firms rather than the sector as a whole.

For green firms, the sectoral profile shifts markedly: several sector, notably utilities and real estate, and to a lesser extent communication services, display predominantly positive ESG betas across horizons, consistent with the idea that stronger ESG spillovers are associated with valuation premia when firms are perceived as more aligned with long-run sustainability objectives, whereas consumer discretionary exhibits the widest dispersion and a clear deterioration in the long-term band (with the distribution tilting negative), indicating that even among greener firms ESG information can be priced unevenly due to heterogeneous exposure to supply-chain and reputational risks and differences in the credibility of ESG improvements. This cross-sector divergence is consistent with the notion that ESG-related intangibles may be underappreciated in the short run but rewarded as markets learn about long-run value creation (Edmans (2011)), and it aligns with the equilibrium mechanism in Pástor, Stambaugh, and Taylor (2021) whereby investor ESG preferences and rising demand for green products generate systematic pricing effects: brown firms face valuation discounts tied to reputational risk, stranded-asset exposure, and capital reallocation away from unsustainable activities, while green firms receive valuation uplifts when positive ESG shocks shift demand fundamentals and strengthen expected long-run cash flows.

Overall, the firm- and sector-level beta decompositions show that the return predictability embedded in ESG connectedness is inherently frequency-specific and sector dependent. In the brown universe, the long-horizon decomposition highlights a persistent penalty concentrated in high-carbon activities: energy exhibits systematically negative betas that remain sizeable at longer horizons, consistent with a gradual repricing of transition risk, stranded-asset exposure, and capital reallocation away from carbon-intensive industries (Ilhan, Sautner, and Vilkov (2021); Pástor, Stambaugh, and Taylor (2021)). Industrials, by contrast, display more heterogeneous short-run responses and a shift toward positive long-horizon betas for a subset of firms, suggesting that transition readiness and credible ESG improvements can translate into forward-looking return premia. In the green universe, ESG connectedness is more often associated with positive and anticipatory betas, particularly in industrials, information technology, and real estate, which is consistent with the view that ESG-related intangibles may be underpriced in the short run but rewarded as markets learn about their long-run value (Edmans (2011)) and with equilibrium mechanisms whereby rising investor preferences for sustainability and demand for green products generate valuation uplifts for ESG-aligned firms (Pástor, Stambaugh, and Taylor (2021)). At the same time, weaker or less stable predictability in sectors such as utilities and financials points to the role of regulatory rigidities and slower adjustment dynamics, reinforcing the importance of sectoral differentiation (Pedersen, Fitzgibbons, and Pomorski (2021)[36]) and temporal variation when evaluating ESG pricing. These patterns also align with the dynamic perspective in Pástor, Stambaugh, and Taylor (2022), which distinguishes expected from realised returns: green firms may have lower expected returns due to taste- and risk-premia effects, yet can exhibit realised outperformance following unexpected shifts in ESG demand or regulation, while brown energy remains exposed to long-run repricing pressures.

The results underscore that frequency-domain, sector-disaggregated ESG signals uncover latent channels of ESG risk and opportunity that are obscured in aggregate analyses, supporting the case for incorporating horizon-specific ESG connectedness measures into both investment decisions and policy assessment (Albuquerque et al. (2020); Pástor, Stambaugh, and Taylor (2021); Pedersen, Fitzgibbons, and Pomorski (2021); Ilhan, Sautner, and Vilkov (2021); Pástor, Stambaugh, and Taylor (2022)).

[36] As shown by Pedersen, Fitzgibbons, and Pomorski (2021), sectoral heterogeneity is central to ESG return dynamics: their ESG-efficient frontier framework implies that sectors such as information technology, industrials, and real estate are more likely to capture a green premium due to stronger ESG alignment, consistent with our positive ESG betas for these green sectors over medium and long horizons.

3.7 Conclusion

We study an aggregate, market-wide measure of ESG connectedness, a systematic risk proxy that captures how ESG news and practices co-move across firms and propagate through the market. Using monthly ESG scores for 334 U.S. firms, we extract the common ESG signal and its spillover intensity via a time-varying dynamic factor framework and then decompose this signal into short- and long-frequency components (following the time–frequency logic of Barigozzi, Hallin, et al. (2021)). The resulting indices quantify, respectively, (i) high-frequency ESG shocks linked to operational adjustments and near-term news, and (ii) slow-moving ESG forces associated with reputation, stakeholder relations, and transition dynamics. By treating ESG connectedness as a systematic factor, rather than firm-specific noise, we evaluate its ability to forecast excess returns for both green and brown firms, showing how predictive content varies meaningfully with horizon and frequency.

Our findings reveal strong evidence of frequency- and firm-type–dependent predictability. For green firms, ESG connectedness does not exhibit significant return predictability in the short term; however, beginning around the 13-month horizon, the predictive power becomes statistically significant and economically meaningful across all frequency bands. This long-horizon effect is most prominent in the long-term ESG connectedness component, where the predictive β peaks at 0.7827 with a highly significant t-statistic of 8.74 at the 18-month horizon. Complementing these return results, robustness checks that replace returns with firm fundamentals show that a 1σ increase in long-frequency connectedness strongly predicts improvements in $\Delta\log(1+\text{ROA})$ and $\Delta\log(1+\text{GPTA})$ at approximately 20 to 24 months horizon (with t-statistics often well above 9), while short-frequency effects become clearly positive only after 17 months horizon. For gross profit margin, coefficients are small early but turn significant over longer horizons. By contrast, $\Delta\log(1+\text{ROE})$ loads negatively, most strongly on the long-frequency component, consistent with equity-financed transition and deleveraging that temporarily expand the equity base faster than earnings.

Overall, markets appear to gradually price ESG benefits for green firms, in line with theories emphasizing the strategic and long-term nature of sustainable investing. Our findings are consistent with Pedersen, Fitzgibbons, and Pomorski (2021), who show that ESG can lower the cost of capital and stimulate real investment, and with Chu et al. (2020), who argue that ESG reduces uncertainty and improves long-run fundamentals.

For brown firms, ESG connectedness shows clear short-horizon return predictability, with effects visible within the first year and long-frequency signals already mattering in the very early months. Robustness checks using fundamentals confirm a two-channel mechanism with distinct timing. ROA improves mainly at the longest horizons, with short-frequency signals turning positive only late and long-frequency effects strengthening toward the end of the window after a brief mid-horizon dip. For gross profit margin, short-frequency effects become economically meaningful from the mid-teens onward, while long-frequency effects appear earlier and remain strong into the longest horizons. GPTA tells the same story: short-frequency gains emerge after several reporting cycles and grow toward the back end, whereas long-frequency effects surface in the mid-teens, soften briefly, and then reassert themselves late. ROE is U-shaped, initially negative in the mid-teens, then turning positive at the longest horizons, consistent with upfront compliance and transition costs (and balance-sheet adjustments) followed by operational and intangible payoffs. Overall, brown firms exhibit strong near-term return predictability but slower translation into profitability, while reputation-driven gains arrive unevenly yet prove durable over multi-year horizons.

Our aggregate analysis, summarised graphically through predictive R^2 across horizons, confirms that short-term ESG connectedness explains a substantial share of return variation at early horizons, while long-term connectedness becomes more informative later on, especially for green firms. This validates the usefulness of frequency decomposition in ESG research and confirms our hypothesis that ESG's return implications are not static but evolve across time and firm characteristics.

These empirical findings both align with and extend the growing body of literature on ESG and asset pricing, including contributions by Albuquerque et al. (2020), Pástor, Stambaugh, and Taylor (2021), Van der Beck (2021) and Avramov, Cheng, et al. (2022). By adopting a frequency-based framework, this study isolates transitory versus persistent components of ESG measures, offering a more granular understanding of how markets incorporate ESG signals across different time horizons and firm types. A key contribution of this analysis lies in its treatment of firm heterogeneity. Unlike prior research (Chu et al. (2020)) that often aggregates green and brown firms, potentially masking important distinctions, our disaggregated approach reveals pronounced asymmetries in return predictability.

At the same time, our evidence of a persistent long-horizon ESG signal in returns is consistent with the dynamic equilibrium mechanism in Avramov, Lioui, et al. (2025), where time-varying ESG demand shocks are a priced risk source and generate sustained return effects, especially over extended horizons, **even when convenience-yield forces may depress expected green returns.

The sector-level decomposition shows that ESG connectedness predicts returns in a way that is both horizon- and industry-dependent, consistent with ESG operating as a systematic risk channel whose pricing varies with firms' technological scope and transition exposure. Within the brown universe, industrials display wide short-term dispersion (at the 12-month horizon) and increasingly positive exposures at longer horizons, suggesting heterogeneous transition paths in which process upgrades and reputational repair gradually translate into returns. By contrast, energy firms exhibit tighter, predominantly negative long-horizon betas, in line with persistent transition and stranded-asset risk being priced more uniformly across the sector. These results reinforce the main in-sample regressions: near-term signals for brown firms are strongest where operational adjustments are most variable (industrials), while long-run penalties remain largest where carbon intensity is structurally entrenched (energy).

For green firms, sectoral patterns are more consistent with the slow accumulation of intangible capital. At a 12-month horizon, predictive content is most evident in innovation-oriented sectors (e.g., information technology and real estate), where ESG investment, product cycles, and investor clientele effects can be transmitted relatively quickly. Over longer horizons, dispersion broadens across most green sectors, with information technology and industrials tending toward positive median betas, while communication services and energy show wider, sometimes negative tails, indicative of divergent strategic execution within sectors even among green-classified firms. Overall, the sector evidence complements the aggregate results: short-frequency connectedness aligns with operational levers that show up sooner in sectors capable of rapid adjustment, whereas long-frequency connectedness captures slower, reputation- and alignment-driven payoffs that are stronger and more pervasive across green sectors and uneven, but ultimately material, among brown industries undergoing transition.

Our empirical evidence answers the central research question: behind the well-documented rating noise, our ESG connectedness measure embeds a slow-moving component that predicts long-horizon returns. In in-sample predictability tests, the statistically significant coefficients reveal positive and economically meaningful betas on excess returns at both the short- and long-term frequencies for both green and brown firms, indicating that near-term operational channels and slow-moving reputation/intangibles are priced. Taken together with the fundamentals robustness, where profitability measures respond most strongly at longer horizons, these results contribute to the literature documenting a positive association between ESG performance and firm profitability. More broadly, the frequency- and sector-aware analysis shows that ESG measures contain valuable forward-looking information about return variation, and that ESG is increasingly priced in a dynamic, non-uniform manner across firms and industries, consistent with recent theoretical and empirical work by Pástor, Stambaugh, and Taylor (2021), Albuquerque et al. (2020), and Pedersen, Fitzgibbons, and Pomorski (2021).

Several avenues for future research remain open. First, a portfolio perspective could directly test the tradability of ESG connectedness as a systematic risk factor. One approach is to sort firms into deciles (or quintiles) each month on short- and long-frequency connectedness, form value- or equal-weighted portfolios, and study long–short spreads (high–minus–low) across horizons. Factor-mimicking portfolios for each frequency band can then be benchmarked against standard models (e.g., CAPM, Fama–French 3/5 factors, Carhart) using alpha tests, spanning/redundancy tests, and Fama–MacBeth risk–price estimates, with attention to turnover, transaction costs, and state dependence (e.g., policy/news regimes, volatility states). Second, event-level identification, exploiting firm-specific ESG news or regulatory shocks, could clarify mechanisms behind spillovers and the timing differences we document. Third, applying the framework internationally would reveal how legal, cultural, and disclosure institutions shape the pricing of ESG-connected risks. Fourth, heterogeneity by investor clientele (e.g., the share of ESG-aware institutions) could explain cross-sectional variation in speed and strength of ESG transmission. Finally, integrating richer text-based measures and machine-learning filters (topic models, transformer embeddings) may sharpen the signal-to-noise ratio in connectedness and enhance out-of-sample portfolio performance.

In conclusion, our research shows that ESG connectedness carries significant predictive power for future returns, but this power is both frequency-dependent and firm-type-specific. The findings underscore that ESG is not merely a corporate responsibility metric, but a financially material factor with profound implications for asset pricing, investment strategy, and policy design.

Appendix C

Chapter 3

C.1 Tables and Figures

Table C.1: **In-Sample Predictive Regressions: Aggregate ESG Connectedness Across Frequencies for Green Firms.** Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

Horizon	Short-Term β_h	Short-Term t-stat	Long-Term β_h	Long-Term t-stat
1	0.0318	0.96	0.3497	0.48
2	0.0434	1.67	0.4259	0.61
3	0.0545**	2.52	0.5239	0.79
4	0.0547**	2.57	0.4578	0.70
5	0.0598**	2.86	0.4405	0.70
6	0.0591**	2.83	0.3751	0.60
7	0.0545**	2.76	0.4669	0.83
8	0.0509**	2.73	0.4697	0.90
9	0.0510**	2.86	0.5034	1.10
10	0.0514**	2.93	0.5819	1.46
11	0.0495**	3.11	0.5762	1.64
12	0.0459**	3.63	0.4863	1.46
13	0.0439**	4.35	0.6216**	2.41
14	0.0403***	5.58	0.6012***	2.73
15	0.0367***	7.38	0.5371**	2.45
16	0.0337***	6.90	0.4654	1.82
17	0.0384***	8.75	0.6970***	9.60
18	0.0382***	7.07	0.7827***	8.74
19	0.0350***	7.76	0.7304***	9.23
20	0.0314***	9.62	0.6638***	11.74
21	0.0295***	9.48	0.6193***	12.49
22	0.0268***	9.82	0.5644***	13.85
23	0.0236***	10.76	0.5081***	16.19
24	0.0208***	11.78	0.4651***	17.59

Table C.2: **In-Sample Predictive Regressions: Aggregate ESG Connectedness Across Frequencies for Brown Firms.** Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

Horizon	**Short-Term**		**Long-Term**	
	β_h	t-stat	β_h	t-stat
1	0.0195	1.47	0.1989	0.61
2	0.0208*	1.92	0.1835	0.61
3	0.0223**	2.38	0.1854	0.68
4	0.0215**	2.35	0.1611	0.61
5	0.0224**	2.53	0.1509	0.60
6	0.0220**	2.52	0.1312	0.53
7	0.0207**	2.44	0.1626	0.70
8	0.0199**	2.43	0.1677	0.77
9	0.0200**	2.62	0.1858	0.96
10	0.0202**	2.80	0.2189	1.30
11	0.0196**	3.07	0.2227	1.53
12	0.0184**	3.64	0.1967	1.44
13	0.0178***	4.54	0.2537**	2.42
14	0.0167***	5.97	0.2522***	2.86
15	0.0155***	8.07	0.2339***	2.74
16	0.0145***	7.88	0.2115**	2.18
17	0.0160***	9.70	0.2948***	10.38
18	0.0154***	8.06	0.3160***	10.13
19	0.0137***	8.82	0.2839***	10.77
20	0.0118***	10.40	0.2489***	13.12
21	0.0106***	10.36	0.2225***	14.17
22	0.0093***	10.93	0.1966***	16.08
23	0.0081***	11.94	0.1731***	18.39
24	0.0069***	12.32	0.1547***	18.10

Table C.3: **Local Projections on ESG Connectedness for Green Firms (Panels A and B).** Dependent variable is $\Delta \log(1{+}F)_{t\to t+h}$, scaled to annualized percentage points. Cells report β_h (per 1σ increase in ESG connectedness); Newey–West t-statistics in parentheses. Statistical significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

Panel A: ROA and GPTA

Horizon	ROA		GPTA	
	Short	Long	Short	Long
1	0.4784* (1.93)	0.7242*** (3.22)	-0.5456 (-0.47)	0.6830 (0.81)
2	0.5338** (2.52)	0.6782*** (2.92)	-0.0167 (-0.03)	0.6232 (1.34)
3	0.3935** (2.00)	0.4869** (2.16)	0.0864 (0.25)	0.4077 (1.13)
4	0.2432 (1.24)	0.3065 (1.53)	-0.1591 (-0.49)	0.0050 (0.01)
5	0.1434 (0.71)	0.2150 (1.30)	-0.0366 (-0.12)	0.0738 (0.24)
6	0.0871 (0.44)	0.1316 (0.89)	0.1320 (0.46)	0.1579 (0.64)
7	0.0348 (0.18)	0.0688 (0.44)	0.1032 (0.39)	0.1086 (0.48)
8	-0.0032 (-0.02)	0.0315 (0.20)	0.0639 (0.24)	0.0519 (0.24)
9	0.0193 (0.10)	0.0295 (0.21)	0.0820 (0.32)	0.0799 (0.39)
10	-0.0252 (-0.15)	-0.0444 (-0.36)	0.0063 (0.03)	-0.0295 (-0.17)
11	-0.0611 (-0.41)	-0.0792 (-0.68)	-0.0457 (-0.25)	-0.0923 (-0.61)
12	-0.0988 (-0.90)	-0.1281 (-1.35)	-0.1761 (-1.37)	-0.2557** (-2.37)
13	-0.1181 (-1.54)	-0.1199 (-1.53)	-0.1351 (-1.18)	-0.1887* (-1.83)
14	-0.1765** (-2.48)	-0.2000*** (-4.85)	-0.1916 (-1.50)	-0.2633*** (-4.21)
15	-0.1847** (-2.21)	-0.2293*** (-8.39)	-0.2517* (-1.78)	-0.3383*** (-7.10)
16	-0.1563** (-2.40)	-0.2041*** (-10.06)	-0.2961** (-2.39)	-0.3836*** (-10.33)
17	-0.0294 (-0.89)	-0.1313** (-2.01)	-0.1165** (-2.36)	-0.3023*** (-3.20)
18	0.0648* (1.75)	0.1027* (1.83)	0.0923 (1.00)	0.1553 (1.08)
19	0.0955*** (3.04)	0.1625*** (3.29)	0.1751** (2.14)	0.3115** (2.35)
20	0.1169*** (4.41)	0.2027*** (4.79)	0.2053*** (3.03)	0.3718*** (3.37)
21	0.1417*** (5.80)	0.2411*** (6.51)	0.2626*** (3.92)	0.4535*** (4.34)
22	0.1515*** (7.88)	0.2545*** (9.94)	0.2624*** (4.82)	0.4628*** (5.59)
23	0.1498*** (9.31)	0.2552*** (13.51)	0.2414*** (5.84)	0.4279*** (7.20)
24	0.1560*** (11.66)	0.2714*** (16.63)	0.1946*** (7.28)	0.3435*** (9.42)

Panel B: GPM and ROE

Horizon	GPM		ROE	
	Short	Long	Short	Long
1	-1.4050 (-0.81)	-1.0518 (-0.64)	-7.3604* (-1.67)	-5.5682 (-1.29)
2	-2.3430 (-1.21)	-1.5729 (-0.89)	-8.2757* (-1.89)	-7.5205* (-1.74)
3	-1.6596 (-1.39)	-1.4259 (-1.08)	-8.5612** (-2.06)	-7.8594* (-1.80)
4	-0.7309 (-1.06)	-0.8252 (-1.15)	-7.9598** (-2.25)	-7.7947** (-2.00)
5	0.4630 (0.65)	-0.2876 (-0.72)	-8.0355** (-2.40)	-7.3408* (-1.89)
6	0.5528 (0.72)	-0.2257 (-0.52)	-8.6732*** (-2.73)	-7.7972* (-1.93)
7	0.2380 (0.37)	-0.4015 (-1.08)	-8.8691*** (-3.01)	-8.1986** (-2.02)
8	0.0820 (0.16)	-0.4613 (-1.48)	-6.9992*** (-3.60)	-7.0958** (-2.49)
9	0.2136 (0.38)	-0.3952 (-1.40)	-1.8600 (-1.06)	-3.6178** (-2.35)
10	0.1079 (0.24)	-0.4276 (-1.86)	0.0696 (0.04)	-1.7159 (-1.61)
11	0.0787 (0.20)	-0.4138** (-2.09)	0.0921 (0.06)	-1.5212* (-1.75)
12	0.0587 (0.15)	-0.4152** (-2.18)	-0.2007 (-0.13)	-1.7641** (-2.45)
13	0.0812 (0.20)	-0.2964 (-1.27)	-0.3389 (-0.24)	-1.5703** (-2.05)
14	0.0541 (0.14)	-0.3003 (-1.40)	-0.5233 (-0.43)	-1.5924*** (-2.67)
15	0.0265 (0.07)	-0.3070 (-1.51)	-0.9332 (-0.88)	-1.7982*** (-3.90)
16	0.0622 (0.20)	-0.2503 (-1.28)	-1.3845 (-1.38)	-2.1903*** (-5.23)
17	0.6715*** (5.49)	0.4451 (1.15)	-0.3393 (-0.48)	-1.9827 (-1.58)
18	0.7856*** (4.08)	1.3193*** (4.48)	0.0058 (0.01)	-0.0985 (-0.12)
19	0.6697*** (4.09)	1.1427*** (4.42)	-0.7354* (-1.89)	-1.1762* (-1.85)
20	0.5490*** (3.79)	0.9522*** (4.11)	-1.5714*** (-7.47)	-2.5208*** (-8.17)
21	0.4350*** (3.37)	0.7510*** (3.66)	-1.7380*** (-26.07)	-2.7720*** (-26.11)
22	0.3304*** (2.85)	0.5820*** (3.12)	-0.7995*** (-7.00)	-1.4748*** (-7.71)
23	0.2012** (2.20)	0.3611** (2.40)	-0.1870*** (-4.55)	-0.3711*** (-5.55)
24	0.0445 (0.83)	0.0691 (0.77)	-0.1417*** (-7.89)	-0.2302*** (-7.52)

Table C.4: **Local Projections on ESG Connectedness for Brown Firms (Panels C and D).** Dependent variable is $\Delta \log(1+F)_{t\to t+h}$, scaled to annualized percentage points. Cells report β_h (per 1σ increase in ESG connectedness); Newey–West t-statistics in parentheses. Significance: * 10%, ** 5%, *** 1%.

Panel C: ROA and GPTA

Horizon	ROA Short	ROA Long	GPTA Short	GPTA Long
1	0.3084 (0.69)	1.1914** (2.19)	0.1489 (0.33)	1.1315** (2.08)
2	0.2529 (0.55)	0.9100** (1.97)	0.2166 (0.45)	0.8122** (2.19)
3	0.4049 (0.88)	0.7825* (1.83)	0.4796 (0.96)	0.7987** (1.96)
4	0.2996 (0.65)	0.3746 (0.88)	0.1942 (0.35)	0.1641 (0.33)
5	0.3206 (0.74)	0.1715 (0.44)	0.3524 (0.75)	0.0950 (0.22)
6	0.2183 (0.57)	−0.0608 (−0.16)	0.3679 (0.89)	−0.0322 (−0.08)
7	−0.0391 (−0.14)	−0.1302 (−0.56)	0.1626 (0.57)	0.0009 (0.00)
8	−0.3718** (−2.06)	−0.3439** (−1.99)	−0.2143 (−1.11)	−0.2552 (−1.37)
9	−0.4837** (−2.49)	−0.4745*** (−2.62)	−0.3048 (−1.48)	−0.3342* (−1.91)
10	−0.5128** (−2.01)	−0.5237** (−2.19)	−0.2909 (−1.07)	−0.3308 (−1.43)
11	−0.4695* (−1.84)	−0.5074** (−2.28)	−0.2359 (−0.88)	−0.3120 (−1.49)
12	−0.4371** (−2.36)	−0.5667*** (−4.69)	−0.2361 (−1.28)	−0.4249*** (−3.53)
13	−0.3447** (−2.17)	−0.4002*** (−2.69)	−0.1417 (−0.80)	−0.2464 (−1.59)
14	−0.3263*** (−3.10)	−0.3893*** (−3.55)	−0.1504 (−1.19)	−0.2486* (−1.77)
15	−0.3111*** (−3.58)	−0.4007*** (−3.87)	−0.1803* (−1.80)	−0.3113** (−2.23)
16	−0.2859*** (−3.63)	−0.3914*** (−3.23)	−0.2542*** (−2.62)	−0.3957** (−2.37)
17	−0.1234*** (−3.39)	−0.1787*** (−5.72)	−0.0718 (−1.29)	−0.1382*** (−3.38)
18	−0.0064 (−0.11)	−0.0046 (−0.08)	0.0880 (1.02)	0.0913 (1.07)
19	0.1169* (1.92)	0.1473** (2.28)	0.2365*** (2.85)	0.2769*** (3.20)
20	0.2509*** (4.13)	0.2932*** (4.57)	0.3567*** (5.09)	0.4110*** (5.55)
21	0.3852*** (6.07)	0.4380*** (7.21)	0.4865*** (6.72)	0.5478*** (7.92)
22	0.4442*** (8.35)	0.5022*** (11.15)	0.5379*** (8.53)	0.6048*** (11.15)
23	0.4361*** (11.49)	0.5031*** (18.27)	0.5109*** (11.15)	0.5806*** (16.37)
24	0.4260*** (14.01)	0.5100*** (23.92)	0.4535*** (12.32)	0.5465*** (19.87)

Panel D: GPM and ROE

Horizon	GPM Short	GPM Long	ROE Short	ROE Long
1	1.6503* (1.89)	2.9104** (2.37)	−2.2131 (−0.95)	0.7017 (0.25)
2	1.0951 (1.08)	1.8749 (1.52)	−1.7211 (−0.94)	−0.0929 (−0.03)
3	1.0527 (1.05)	1.2717 (0.99)	−0.7129 (−0.46)	0.5801 (0.30)
4	0.6410 (0.69)	0.5281 (0.42)	−0.7472 (−0.49)	−0.1923 (−0.12)
5	0.1169 (0.15)	−0.1355 (−0.12)	−1.0129 (−0.71)	−0.9648 (−0.67)
6	−0.3800 (−0.53)	−0.8016 (−0.83)	−1.4462 (−1.09)	−1.8582 (−1.45)
7	−1.0273 (−1.57)	−1.2755* (−1.85)	−1.8278** (−2.02)	−1.5542 (−1.48)
8	−1.6548*** (−3.14)	−1.7192*** (−3.37)	−2.4606*** (−3.63)	−2.0793** (−2.28)
9	−1.9179*** (−4.37)	−2.0329*** (−4.59)	−2.7102*** (−3.55)	−2.7112*** (−3.44)
10	−1.9251*** (−4.14)	−2.0114*** (−4.09)	−2.8415*** (−2.79)	−2.6977** (−2.25)
11	−1.5351*** (−3.57)	−1.6112*** (−3.74)	−2.9034*** (−2.74)	−2.8581** (−2.26)
12	−1.0304*** (−3.44)	−1.2833*** (−5.63)	−3.1900*** (−4.11)	−3.3566*** (−3.75)
13	−0.5925** (−2.36)	−0.7682*** (−3.08)	−3.0055*** (−5.80)	−3.0599*** (−4.30)
14	−0.4780** (−2.15)	−0.6426** (−2.42)	−2.4844*** (−6.82)	−2.5655*** (−4.70)
15	−0.4742** (−2.34)	−0.6295** (−2.55)	−2.0476*** (−9.51)	−2.1228*** (−6.79)
16	−0.5004** (−2.46)	−0.6598** (−2.50)	−1.5458*** (−10.39)	−1.6802*** (−11.50)
17	−0.3461*** (−4.75)	−0.4267*** (−4.14)	−1.0382*** (−7.40)	−1.2081*** (−8.30)
18	−0.2424*** (−5.69)	−0.2643*** (−6.62)	−0.6625*** (−3.97)	−0.6345*** (−3.47)
19	−0.0661** (−2.12)	−0.0661* (−1.89)	−0.0660 (−0.33)	−0.0342 (−0.15)
20	0.1638*** (3.66)	0.1762*** (4.00)	0.3709** (2.14)	0.4254** (2.16)
21	0.3330*** (9.33)	0.3706*** (12.32)	0.6870*** (4.19)	0.8388*** (5.42)
22	0.4480*** (19.02)	0.4971*** (35.42)	0.8506*** (9.38)	0.9511*** (11.42)
23	0.4780*** (22.41)	0.5398*** (26.17)	0.9797*** (22.56)	1.1228*** (33.69)
24	0.5006*** (21.43)	0.5808*** (24.74)	1.0295*** (23.93)	1.1489*** (28.75)

Table C.5: **In-Sample Predictive Regressions: ESG Connectedness Across Frequencies for Green Firms.** Wald tests and p-values are reported. Statistical significance at the 10%, 5%, and 1% levels (based on the Wald test) is indicated by *, **, and ***.

Horizon	Short-Term				Long-Term			
	β_h	t-stat	Wald Stat	p-value	β_h	t-stat	Wald Stat	p-value
1	0.0318	0.96	3.1881^{*}	0.0742	0.3497	0.48	4.0521^{**}	0.0441
2	0.0434	1.67	1.6847	0.1943	0.4259	0.61	3.4676^{*}	0.0626
3	0.0545^{**}	2.52	0.5053	0.4772	0.5239	0.79	2.3838	0.1226
4	0.0547^{**}	2.57	0.4925	0.4828	0.4578	0.70	3.4139^{*}	0.0647
5	0.0598^{**}	2.86	0.0828	0.7736	0.4405	0.70	3.3640^{*}	0.0666
6	0.0591^{**}	2.83	0.0010	0.9747	0.3751	0.60	3.3453^{*}	0.0674
7	0.0545^{**}	2.76	0.0277	0.8679	0.4669	0.83	1.7720	0.1831
8	0.0509^{**}	2.73	0.0379	0.8456	0.4697	0.90	1.4520	0.2282
9	0.0510^{**}	2.86	0.2861	0.5927	0.5034	1.10	0.8558	0.3549
10	0.0514^{**}	2.93	0.9669	0.3254	0.5819	1.46	0.1584	0.6907
11	0.0495^{**}	3.11	1.7475	0.1862	0.5762	1.64	0.0045	0.9463
12	0.0459^{**}	3.63	1.7886	0.1811	0.4863	1.46	0.0719	0.7885
13	0.0439^{**}	4.35	2.3180	0.1279	0.6216^{**}	2.41	0.2589	0.6109
14	0.0403^{***}	5.58	2.4869	0.1148	0.6012^{***}	2.73	0.6675	0.4139
15	0.0367^{***}	7.38	2.6287	0.1049	0.5371^{**}	2.45	0.7923	0.3734
16	0.0337^{***}	6.90	2.4027	0.1211	0.4654	1.82	0.5199	0.4709
17	0.0384^{***}	8.75	4.9601^{**}	0.0259	0.6970^{***}	9.60	4.0043^{**}	0.0454
18	0.0382^{***}	7.07	6.9167^{***}	0.0085	0.7827^{***}	8.74	9.0315^{***}	0.0027
19	0.0350^{***}	7.76	7.3787^{***}	0.0066	0.7304^{***}	9.23	11.7203^{***}	0.0006
20	0.0314^{***}	9.62	6.1284^{**}	0.0133	0.6638^{***}	11.74	11.3300^{***}	0.0008
21	0.0295^{***}	9.48	6.7750^{***}	0.0092	0.6193^{***}	12.49	13.6420^{***}	0.0002
22	0.0268^{***}	9.82	6.6741^{***}	0.0098	0.5644^{***}	13.85	14.7825^{***}	0.0001
23	0.0236^{***}	10.76	5.5321^{**}	0.0187	0.5081^{***}	16.19	12.6604^{***}	0.0004
24	0.0208^{***}	11.78	3.6392^{*}	0.0564	0.4651^{***}	17.59	8.2956^{***}	0.0040

Table C.6: **In-Sample Predictive Regressions: ESG Connectedness Across Frequencies for Brown Firms.** Wald test and p-values are included to assess statistical significance. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***.

Horizon	Short-Term				Long-Term			
	β_h	t-stat	Wald Stat	p-value	β_h	t-stat	Wald Stat	p-value
1	0.0195	1.47	2.7295^{*}	0.0985	0.1989	0.61	4.2168^{**}	0.0400
2	0.0208^{*}	1.92	1.5924	0.2070	0.1835	0.61	3.9166^{**}	0.0478
3	0.0223^{**}	2.38	0.5964	0.4399	0.1854	0.68	2.9284^{*}	0.0870
4	0.0215^{**}	2.35	0.7686	0.3807	0.1611	0.61	4.1370^{**}	0.0420
5	0.0224^{**}	2.53	0.2732	0.6012	0.1509	0.60	4.1351^{**}	0.0420
6	0.0220^{**}	2.52	0.0346	0.8525	0.1312	0.53	4.1503^{**}	0.0416
7	0.0207^{**}	2.44	0.0005	0.9815	0.1626	0.70	2.5716	0.1088
8	0.0199^{**}	2.43	0.0148	0.9033	0.1677	0.77	2.0787	0.1494
9	0.0200^{***}	2.62	0.2996	0.5841	0.1858	0.96	1.2974	0.2547
10	0.0202^{***}	2.80	1.2863	0.2567	0.2189	1.30	0.3600	0.5485
11	0.0196^{***}	3.07	2.8039^{*}	0.0940	0.2227	1.53	0.0379	0.8456
12	0.0184^{***}	3.64	3.5087^{*}	0.0610	0.1967	1.44	0.0819	0.7748
13	0.0178^{***}	4.54	5.3037^{**}	0.0213	0.2537^{**}	2.42	0.3844	0.5353
14	0.0167^{***}	5.97	6.4510^{**}	0.0111	0.2522^{***}	2.86	1.1578	0.2819
15	0.0155^{***}	8.07	7.5249^{***}	0.0061	0.2339^{***}	2.74	1.6238	0.2026
16	0.0145^{***}	7.88	7.0715^{***}	0.0078	0.2115^{**}	2.18	1.2224	0.2689
17	0.0160^{***}	9.70	13.1114^{***}	0.0003	0.2948^{***}	10.38	5.6983^{**}	0.0170
18	0.0154^{***}	8.06	17.7780^{***}	0.0000	0.3160^{***}	10.13	11.2489^{***}	0.0008
19	0.0137^{***}	8.82	19.0654^{***}	0.0000	0.2839^{***}	10.77	13.8051^{***}	0.0002
20	0.0118^{***}	10.40	15.7011^{***}	0.0001	0.2489^{***}	13.12	12.7455^{***}	0.0004
21	0.0106^{***}	10.36	17.9447^{***}	0.0000	0.2225^{***}	14.17	15.1965^{***}	0.0001
22	0.0093^{***}	10.93	18.9086^{***}	0.0000	0.1966^{***}	16.08	16.8335^{***}	0.0000
23	0.0081^{***}	11.94	16.6547^{***}	0.0000	0.1731^{***}	18.39	14.4979^{***}	0.0001
24	0.0069^{***}	12.32	11.5280^{***}	0.0007	0.1547^{***}	18.10	9.3202^{***}	0.0023

C.2 Appendix B: Figures

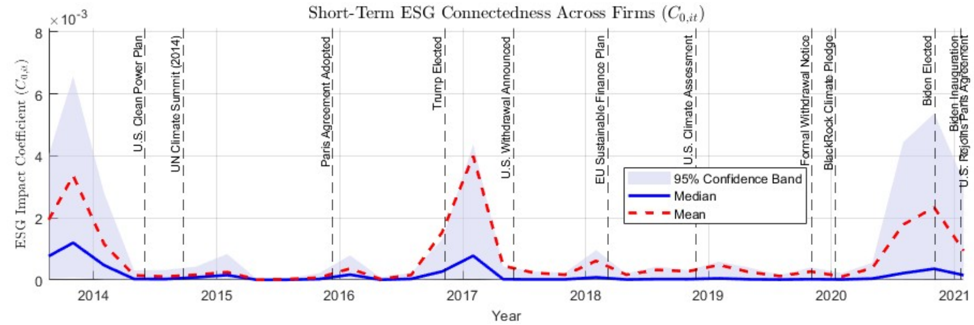


Figure C.1: **Short-Term ESG Connectedness Across Green Firms (2013–2021).** This figure displays the short-term ESG connectedness across green firms, with the 95% confidence band (shaded area), the median (blue line), and the mean (red dashed line).

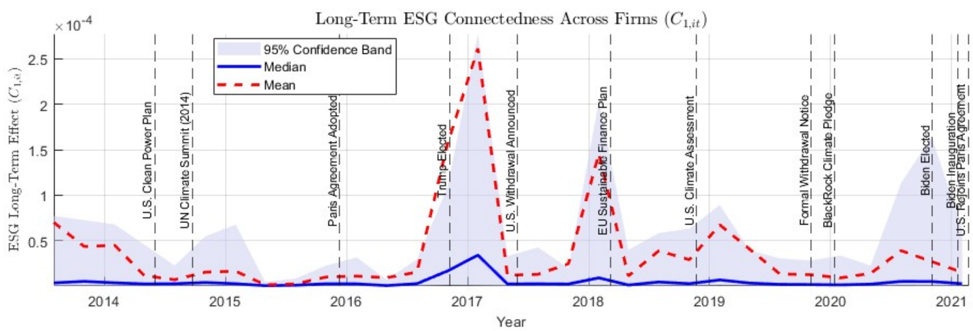


Figure C.2: **Long-Term ESG Connectedness Across Green Firms (2013–2021).** This figure presents the long-term ESG connectedness across green firms, with the 95% confidence band (shaded area), the median (blue line), and the mean (red dashed line).

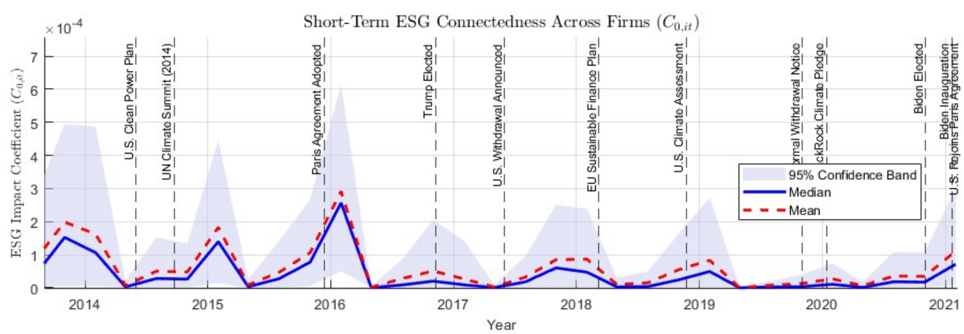


Figure C.3: **Short-Term ESG Connectedness Across Brown Firms (2013–2021).** This figure displays the short-term ESG connectedness across brown firms, with the 95% confidence band (shaded area), the median (blue line), and the mean (red dashed line).

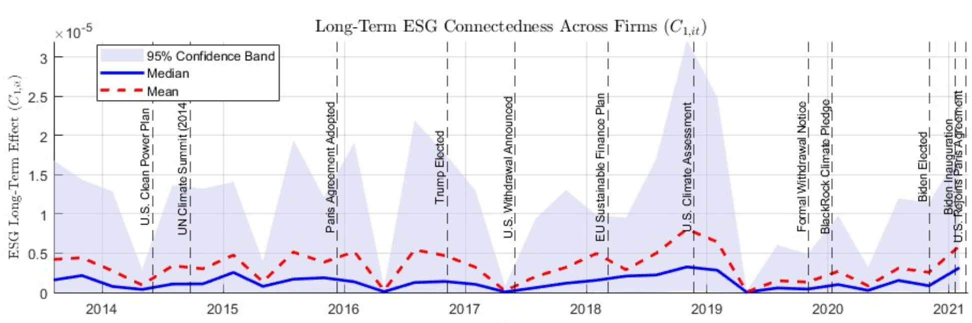
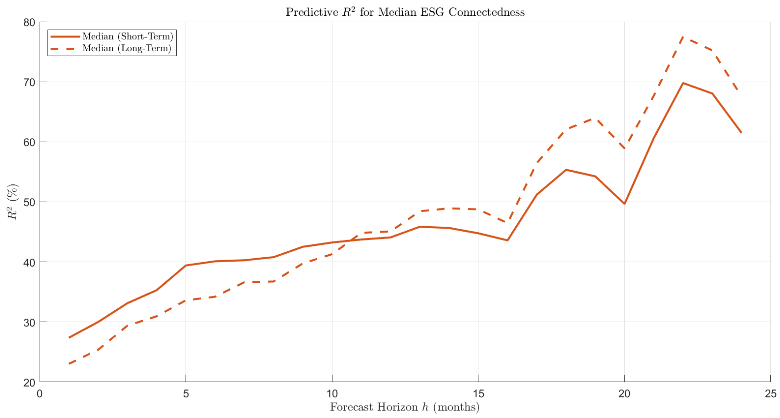
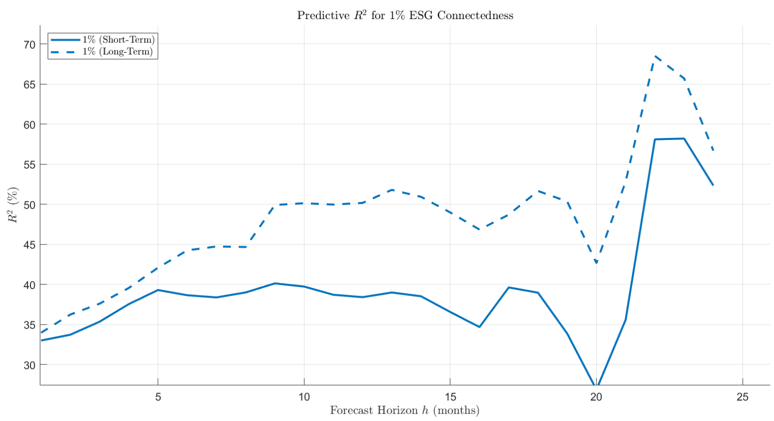


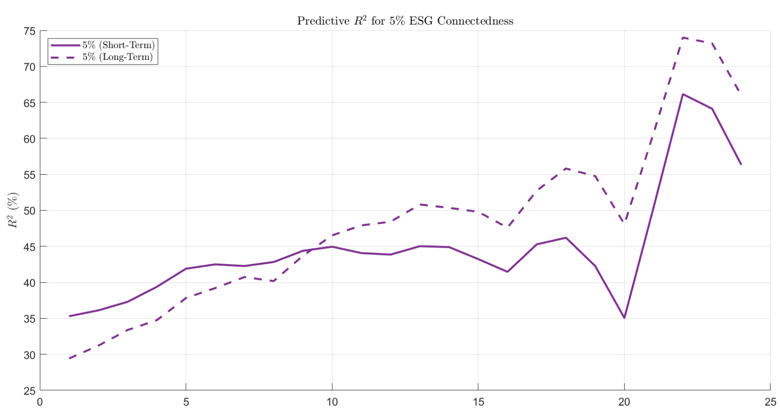
Figure C.4: **Long-Term ESG Connectedness Across Brown Firms (2013–2021).**



(a) Predictive R^2 of monthly market excess returns for green firms using *median* ESG connectedness.

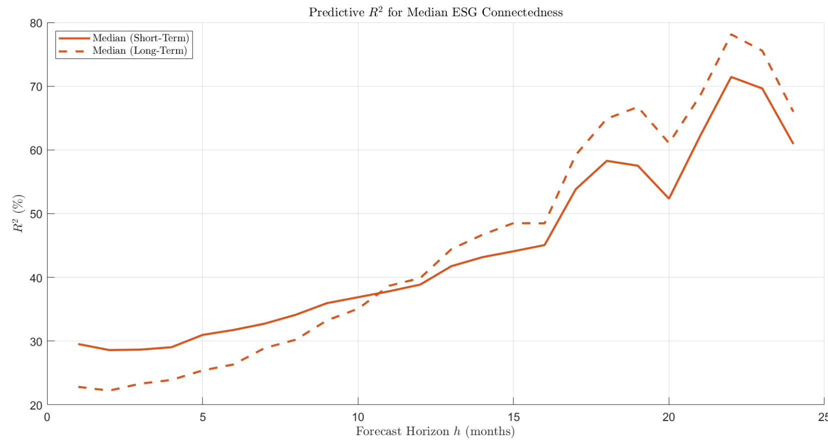


(b) Predictive R^2 of monthly market excess returns for green firms using the *1% quantile* of ESG connectedness.

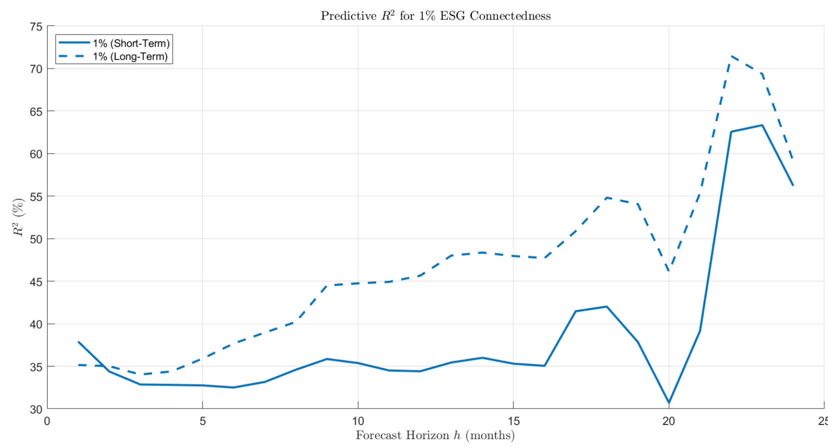


(c) Predictive R^2 of monthly market excess returns for green firms using the *5% quantile* of ESG connectedness.

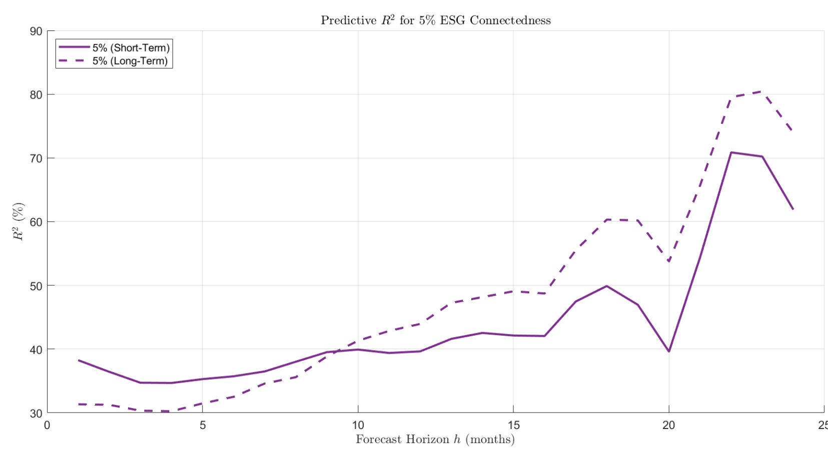
Figure C.5: **Predictive R^2 of monthly market excess returns for green firms using ESG connectedness (median, 1% and 5% quantiles).**



(a) Predictive R^2 of Monthly Market Excess Returns for Brown Firms Using Median ESG Connectedness.

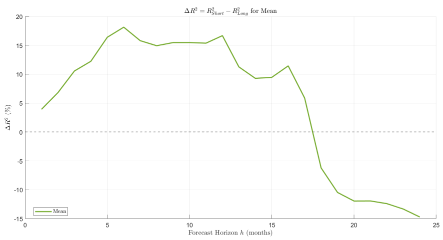


(b) Predictive R^2 of Monthly Market Excess Returns for Brown Firms Using 1% Quantile ESG Connectedness.

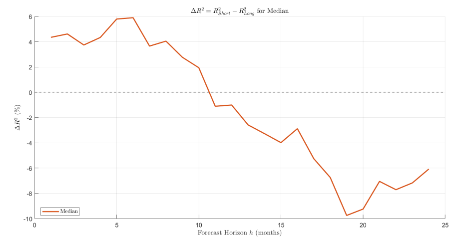


(c) Predictive R^2 of Monthly Market Excess Returns for Brown Firms Using 5% Quantile ESG Connectedness.

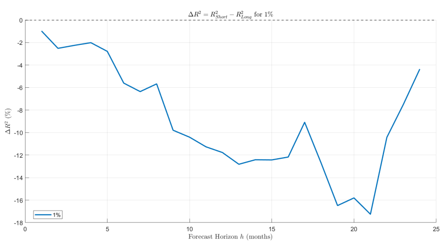
Figure C.6: **Predictive R^2 of Monthly Market Excess Returns for Brown Firms Using ESG Connectedness (Median, 1% and 5% Quantiles).**



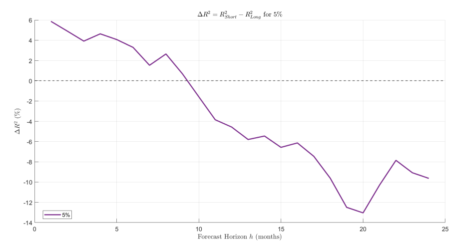
(a) ΔR_h^2 for **Mean** connectedness



(b) ΔR_h^2 for **Median** connectedness

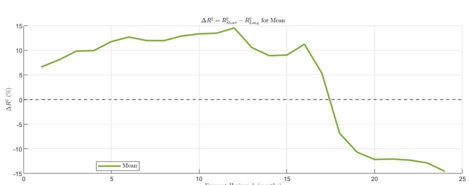


(c) ΔR_h^2 for **1% quantile**

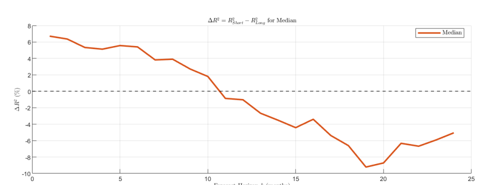


(d) ΔR_h^2 for **5% quantile**

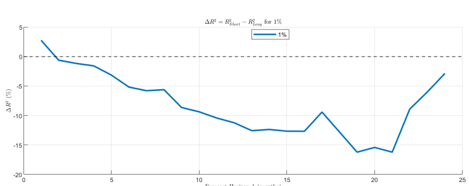
Figure C.7: **Difference in explanatory power,** $\Delta R_h^2 \equiv R^2_{\text{Short},h} - R^2_{\text{Long},h}$, for green firms across forecast horizons h. Positive values indicate that *short-term* ESG connectedness explains more variation than the long-term component; negative values indicate *long-term* dominance.



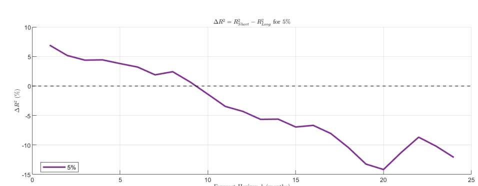
(a) ΔR_h^2 for **Mean** connectedness



(b) ΔR_h^2 for **Median** connectedness



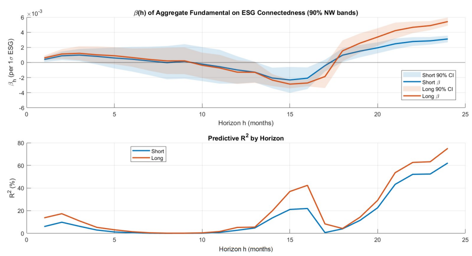
(c) ΔR_h^2 for **1% quantile**



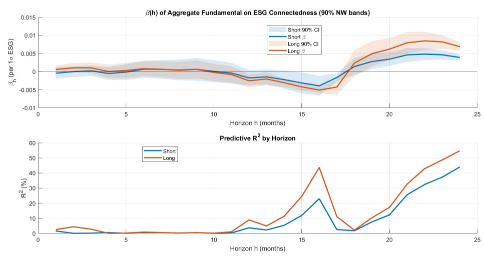
(d) ΔR_h^2 for **5% quantile**

Figure C.8: **Difference in explanatory power,** $\Delta R_h^2 \equiv R^2_{\text{Short},h} - R^2_{\text{Long},h}$, for brown firms across forecast horizons h. Positive values indicate that *short-term* ESG connectedness explains more variation than the long-term component; negative values indicate *long-term* dominance.

Panel A: ROA and GPTA

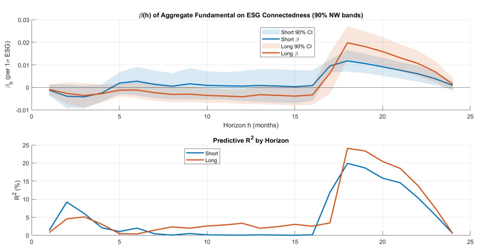


(a) ROA: β_h and predictive $R^2(h)$

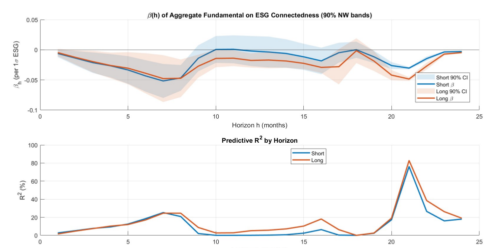


(b) GPTA: β_h and predictive $R^2(h)$

Panel B: GPM and ROE



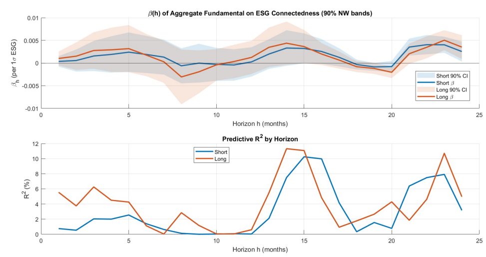
(c) GPM: β_h and predictive $R^2(h)$



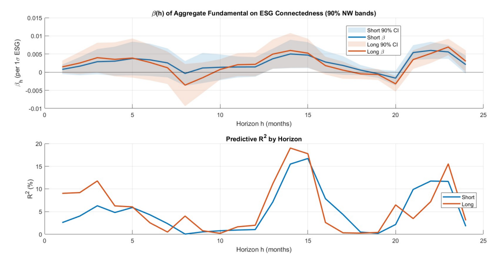
(d) ROE: β_h and predictive $R^2(h)$

Figure C.9: **Local projections for green firms.** Panel A shows horizon-specific coefficients β_h of ESG connectedness (short- and long-frequency components) and the associated predictive $R^2(h)$ for ROA and GPTA. Panel B reports the corresponding results for GPM and ROE.

Panel C: ROA and GPTA (brown firms)

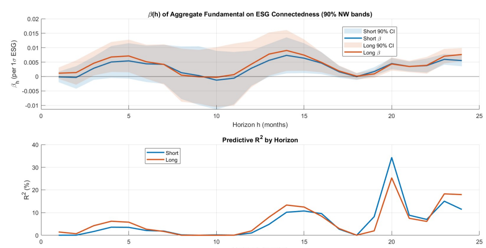


(a) ROA: β_h and predictive $R^2(h)$

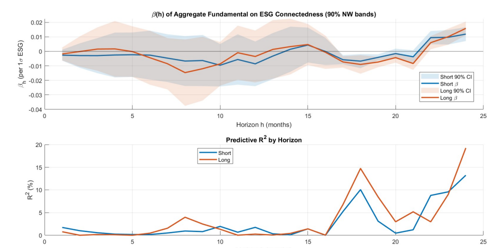


(b) GPTA: β_h and predictive $R^2(h)$

Panel D: GPM and ROE (brown firms)

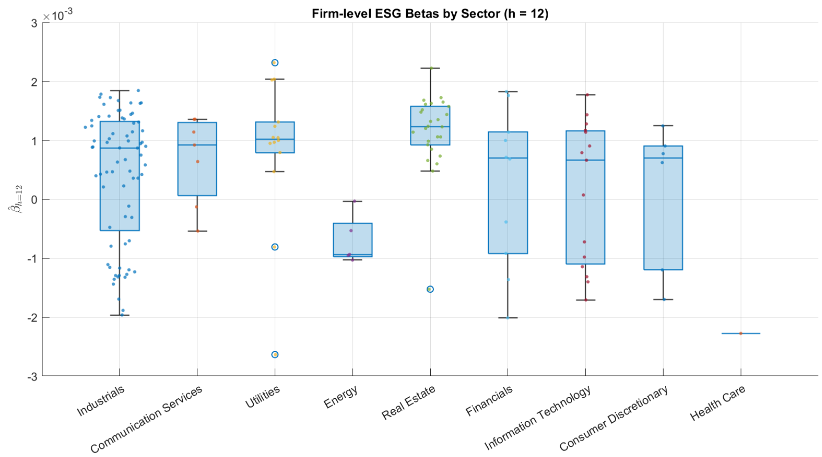


(c) GPM: β_h and predictive $R^2(h)$

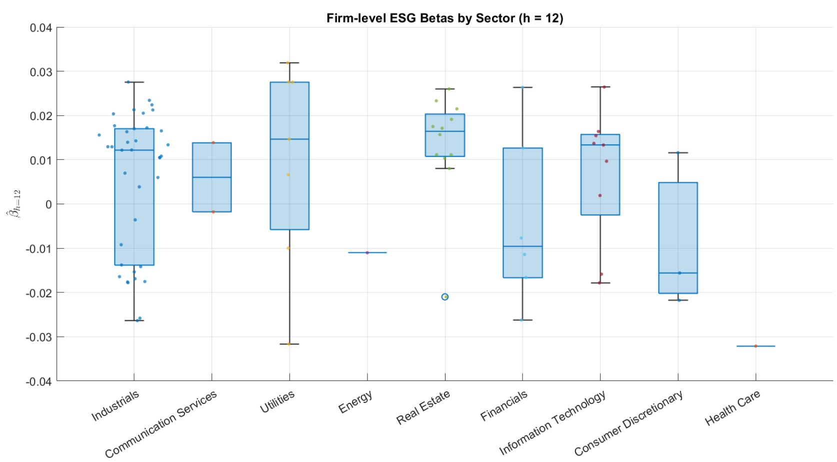


(d) ROE: β_h and predictive $R^2(h)$

Figure C.10: **Local projections for brown firms.** Panel C reports horizon-specific coefficients β_h of ESG connectedness (short- and long-frequency components) and predictive $R^2(h)$ for ROA and GPTA. Panel D reports the corresponding results for GPM and ROE.

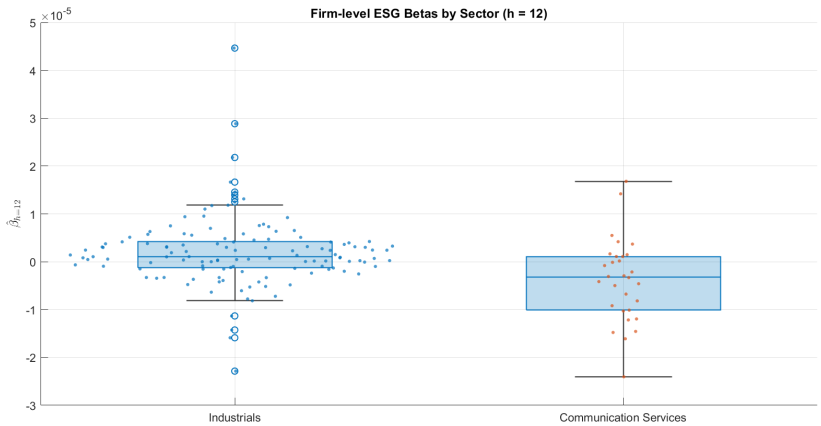


(a) Short-term frequency ($h = 12$).

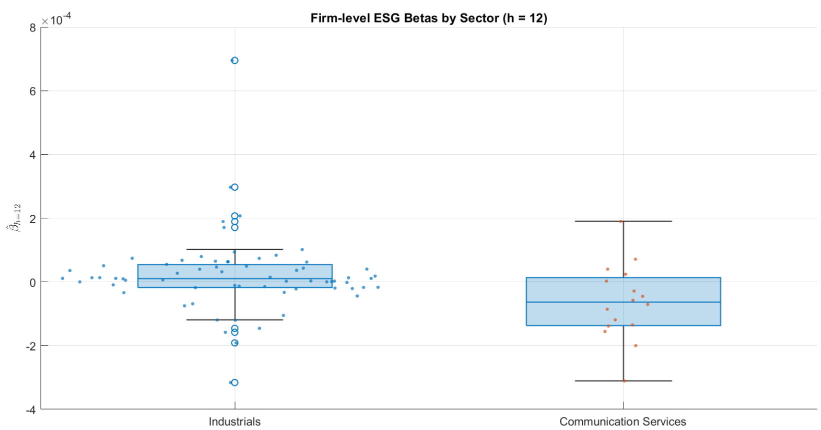


(b) Long-term frequency ($h = 12$).

Figure C.11: **Distribution of Sector-Level ESG Betas for Green Firms.** The panels display the distribution of statistically significant ESG beta coefficients across sectors using (a) short-term and (b) long-term frequency components of ESG connectedness. The forecast horizon is fixed at 12 months.



(a) Short-term frequency ($h = 12$).



(b) Long-term frequency ($h = 12$).

Figure C.12: **Distribution of Sector-Level ESG Betas for Brown Firms.** The panels display the distribution of statistically significant ESG beta coefficients across sectors using (a) short-term and (b) long-term frequency components of ESG connectedness. The forecast horizon is fixed at 12 months.

Chapter 4

Concluding Remarks and Further Developments

This thesis brings together three empirical studies that collectively deepen our understanding of how sustainability, climate risk, and environmental performance shape firm outcomes, financial stability, and market pricing within the U.S. economy. Taken together, these chapters examine how climate- and sustainability-related forces operate through three interconnected channels: the likelihood of corporate failure, the pricing of climate and policy risk in financial markets, and the informational value embedded in ESG signals. By combining firm-level analyses with market-wide perspectives and employing advanced econometric frameworks, the thesis demonstrates that these forces are not merely peripheral considerations, but represent core drivers of corporate vulnerability, investor behaviour, and return dynamics.

A central message emerges clearly from the thesis: sustainability and climate risks are financially material, but their effects are heterogeneous, context-dependent, and horizon-specific. Their impact varies across sectors, geographic locations, firm characteristics, and time horizons, and cannot be adequately captured by uniform or static modelling approaches. This insight provides a unifying interpretation across all empirical chapters and contributes to a more nuanced understanding of how sustainability considerations are embedded in modern financial systems.

Reflecting on the research process, the empirical findings both confirm and refine the initial expectations motivating the thesis. While prior literature suggested that climate risk should be financially relevant, the results demonstrate that its manifestation is more complex than anticipated. In particular, the evidence reveals that (i) exposure to climate and sustainability risk does not translate into uniform outcomes across firms or sectors, (ii) financial markets do price climate-related risks, but in ways that depend critically on regional and institutional heterogeneity, and (iii) ESG information, despite concerns about measurement error, contains economically meaningful signals once analysed through an appropriate time–frequency lens. These findings highlight the importance of moving beyond aggregate or static representations of climate risk towards more granular, dynamic, and multi-dimensional frameworks.

Chapter 1 develops a comprehensive analysis of corporate failure risk among U.S. energy, highly energy-dependent, and non-energy firms. Using logit, Cox survival models, and complementary network analysis, the study demonstrates that failure risk in the energy sector is not uniformly higher or lower than in other sectors; rather, it is context-specific and shaped by leverage, commodity price volatility, environmental pressures, and evolving regulatory dynamics. Environmental indicators, particularly ESG scores and CO_2 emissions, play a meaningful role in predicting corporate resilience, highlighting the increasing relevance of sustainability exposures in distress modelling. This chapter advances the corporate failure literature by (i) explicitly modelling sectoral heterogeneity, (ii) incorporating environmental indicators rarely used in survival frameworks, and (iii) providing dynamic evidence of how failure risk evolves over time.

Chapter 2 examines how U.S. equity markets price climate-related risks using the three-pass methodology of Giglio and Xiu (2021). A major innovation is the introduction of U.S. state-level climate and macro indicators, recognising that climate exposure and policy capacity are geographically uneven. The results show that both transition and physical climate risks are priced, alongside broader uncertainty and political polarisation factors, and that pricing remains robust across alternative factor specifications. The findings underline that ignoring regional climate heterogeneity understates risk and leads to suboptimal portfolio allocation. This chapter enriches empirical asset pricing by embedding climate risk in a richer factor environment and offering policy-relevant insights regarding disclosure, risk management, and regulatory design.

Lastly, Chapter 3 investigates whether ESG information contains a meaningful market signal once its well-documented rating noise is acknowledged. Using a dynamic factor and frequency-domain framework, the chapter extracts ESG connectedness as a systematic market factor and separates fast-moving and slow-moving ESG components. The results reveal strong evidence of horizon- and firm-type dependence: brown firms exhibit earlier and stronger long-horizon predictability, while green firms display more powerful long-horizon effects transmitted through long-frequency ESG connectedness. The chapter also connects ESG to firm fundamentals, showing that ESG benefits materialise most clearly in profitability improvements over longer horizons. This work contributes to the ESG-asset pricing literature by demonstrating that ESG signals are informative, dynamic, and frequency-dependent, and by emphasising firm heterogeneity as a key transmission channel.

Overall, this thesis advances sustainable finance research in three principal ways. First, it shows that sustainability and climate exposures are not peripheral but structurally embedded in corporate stability, risk, and returns. Second, it demonstrates that risk manifestation is inherently heterogeneous, across sectors, geographies, and time horizons, challenging one-size-fits-all modelling approaches. Third, it integrates environmental indicators, regional granularity, and time-frequency methods into traditionally financial frameworks, offering both methodological innovation and substantive insights.

The empirical findings carry important implications for both policy and financial markets. From a regulatory perspective, the results of Chapter 1 suggest that corporate stability frameworks should explicitly incorporate environmental and sector-specific risk exposures, particularly in energy-intensive industries. The evidence from Chapter 2 highlights the need for more granular climate disclosure and greater coordination of climate policy across U.S. states, as regional heterogeneity materially affects risk pricing and capital allocation. From a market perspective, the findings indicate that investors already recognise and price climate-related risks, but may benefit from improved measurement and transparency. Finally, the results of Chapter 3 support the case for enhancing the consistency and comparability of ESG reporting, as capital markets appear to respond to sustainability information when it reflects persistent, long-run fundamentals.

Despite these contributions, the thesis is subject to several limitations that provide opportunities for further research. First, the measurement of climate and ESG variables remains imperfect, with potential noise and inconsistencies across data sources. Second, while the empirical frameworks employed address several econometric challenges, issues related to causality and endogeneity cannot be fully eliminated. Third, the analysis focuses on the U.S. context, which, while highly relevant, may limit the generalisability of the findings to other institutional environments. Recognising these limitations is essential for interpreting the results and for guiding future empirical work.

This thesis also opens multiple avenues for future inquiry. For Chapter 1, future research could explore spillover and contagion dynamics between the energy sector and the broader economy, potentially developing early-warning frameworks for systemic risk. Richer environmental datasets and firm-level transition readiness metrics would further refine sector-specific distress modelling. For Chapter 2, constructing improved state-level climate transition indices using text analytics and machine-learning techniques would enhance risk measurement precision, while incorporating frequency-domain approaches could shed light on how climate risk is priced across different investment horizons. For Chapter 3, future work could examine the tradability of ESG connectedness through portfolio strategies, investigate causal mechanisms using regulatory shocks or natural experiments, and extend the analysis to international settings. Additionally, incorporating investor heterogeneity and AI-based text-derived ESG measures would deepen our understanding of how sustainability information is processed and priced in financial markets.

In conclusion, this thesis demonstrates that sustainability risks are neither abstract nor uniform; they are quantifiable, priced, and consequential for financial stability and asset valuation. By integrating survival modelling, advanced asset-pricing techniques, and innovative ESG analytics, the thesis provides a comprehensive and empirically grounded perspective on how climate and sustainability forces shape the evolving financial landscape. In doing so, it contributes to a more realistic and forward-looking understanding of financial systems, supporting the development of more resilient, informed, and sustainable economic outcomes.

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