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Climate Risk Through the Looking Glass

An Exploratory Analysis of Whether Climate Risks Are Priced into the Swedish Stock Market Using News-Based Factors and Asset Pricing Models

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Abstract

As climate change increasingly challenges global economies, this thesis explores whether climate risks are reflected in financial markets, with a specific focus on the Swedish equity market. This research analyses a comprehensive dataset of Swedish news articles and financial data from January 1, 2000, to December 31, 2023, employing advanced unsupervised machine learning techniques that integrate Latent Dirichlet Allocation with traditional asset pricing models. This approach constructs factors to capture market perceptions of climate risks, specifically Swedish Climate Policies, Energy Transition Policies, International Climate Agreements, and Global Warming, across different periods. The findings reveal a distinct "brown premium", where stocks with greater negative sensitivities to energy transition policies yield higher returns. Notably, this effect intensified following the Paris Agreement, highlighting active market pricing of policy-induced risks as awareness and regulatory commitments deepened globally. Conversely, physical climate risks like global warming do not show similar pricing effects, suggesting a market differentiation between immediate policy-driven risks and more generalized long-term environmental challenges.

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1 Introduction

Do climate risks influence stock market valuations? Specifically, are investors in the Swedish stock market pricing in the risks associated with climate change? As the realities of climate change become increasingly evident, understanding its impact on financial markets is crucial. Climate risk, covering both physical risks from environmental changes and transition risks from policy and technology shifts towards a low-carbon economy, has become a significant concern for investors, firms, and regulators worldwide (Engle et al., 2020). Accurate pricing of these risks is essential for assessing market efficiency, optimizing investment strategies, and aligning financial goals with sustainability objectives.

While research has addressed climate risk pricing in the U.S. and broader European contexts, the nuances of smaller, environmentally progressive markets like Sweden have remained underexplored. Sweden, known for its robust climate policies and strong emphasis on corporate social responsibility (CSR) and environmental, social, and governance (ESG) practices, presents a unique landscape (Nasdaq, 2023). The closest investigation into climate risk in Sweden has been a joint analysis by the Financial Supervisory Authority (Finansinspektionen) and the Central Bank of Sweden (Sveriges Riksbank) (Sveriges Riksbank, 2022), which predominantly focused on the banking sector. Consequently, the broader implications of climate risks for the Swedish equity market have yet to be thoroughly examined. This study extends that focus by providing an analysis of whether both physical and transition climate risks are integrated into asset pricing across various sectors in Sweden, thereby offering valuable insights for local investors, firms, and policymakers, as well as lessons for other similarly positioned markets.

By focusing on the Swedish market, I aim to uncover how climate-related risks are perceived and integrated into asset valuations in Sweden, a country widely recognized for its leadership in climate action. To investigate this, I employ advanced textual analysis techniques in the field of natural language processing (NLP). This approach analyses a dataset of news articles from prominent Swedish outlets from January 1, 2000, to December 31, 2023. Key words related to climate risks are initially identified using the term frequency-inverse document frequency (TF-IDF) method applied to authoritative climate reports. These words guide the selection of relevant articles, which are then analyzed using the Latent Dirichlet Allocation (LDA) method, an unsupervised machine learning technique, to categorize them into topics that reflect various aspects of climate risk (Blei et al., 2003). These topics create time-series measures that act as proxies for market sensitivity to climate risks.

The relationship between these measures and stock returns is analyzed using Fama-French asset pricing models and a detailed portfolio sorting analysis. This approach examines how portfolios, sorted by their sensitivity to climate risks, perform relative to each other while considering established risk factors in asset pricing. By categorizing stocks based on their exposure to climate risks and assessing their returns, the study explores potential non-linear relationships between expected returns and levels of climate risk exposure, providing insights into whether these risks are integrated into market valuations.

Findings suggest that the constructed factor for energy transition policies significantly influences asset pricing within the Swedish stock market, with these effects becoming more pronounced following the Paris Agreement in 2015. Over the entire study period, portfolios negatively sensitive to energy transition policies achieve higher abnormal annual returns of between 3.1% and 4.3%. Specifically, before the Paris Agreement, these firms earn approximately 4.3% higher abnormal returns annually, which increases to about 5.9% annually after the agreement. This pattern is consistent with a "brown premium", where investors require higher returns for holding firms that are more exposed to transition risks. This pattern holds across various Fama-French models and both quintile and decile portfolio analyses. However, other climate-related factors like International Climate Agreements and Global Warming have not shown similar pricing impacts, highlighting the unique response of the Swedish market to energy transition narratives.

This study enhances existing research on climate risk pricing beyond larger economies, providing new insights into how such risks are perceived and integrated into a market known for its strong commitment to sustainability. To the best of my knowledge, it is also the first to focus on the Swedish market and to employ news discourse as a measure of climate risk. It not only enriches the academic discourse but also deepens our understanding of sustainable finance in environments heavily focused on ESG.

From here, the thesis is organized into eight chapters. Chapter 2 provides a background overview, defining climate risks and reviewing their pricing in financial markets, along with the challenges involved in measuring these risks. Chapter 3 surveys the existing literature on climate risk integration within asset pricing models and the importance of investigating climate risk. Chapter 4 outlines the methodology for textual analysis, describing how natural language processing (NLP) techniques are applied to develop climate risk factors from Swedish news media. Chapter 5 details the asset pricing framework, introducing the Fama-French models, the data sources used, and the metrics employed to evaluate the relationships between factors and stock performance. Chapter 6 presents the empirical analysis, combining the developed climate risk and Fama-French factors to examine their relationship with stock returns through regression-based asset pricing models and portfolio sorting analysis. Chapter 7 reports the results of these analyses, presenting how climate risks are reflected in stock market performance. Finally, Chapter 8 summarizes and discusses the validity and limitations of the methods used and offers suggestions for future research, and Chapter 9 concludes the thesis.

2 Background

Climate risk has become recognized as a major factor influencing financial markets globally, potentially affecting asset values and investment decisions. As climate-related events become more frequent and severe and the world moves towards a greener low-carbon economy, both uncertainties and opportunities are arising for regulators, businesses, and investors. The coming sections will address climate risks, their impact on financial markets, the roles of the brown and green premium, and Sweden's distinctive policy environment. Firstly, let's clarify what is meant by climate risks.

Physical Risks

Physical risks from climate change are direct results of the physical impacts associated with climate and weather-related events. These risks are primarily categorized into 'acute' and 'chronic' risks. Acute physical risks include events such as storms, wildfires, floods, and other severe weather phenomena that can cause immediate and extensive damage to physical assets and infrastructures. Chronic risks, on the other hand, refer to long-term shifts in climate patterns like rising sea levels, increasing temperatures, and changing precipitation patterns, which gradually impact ecosystems, water resources, agricultural productivity, and overall human health (IMF, 2020). The financial implications of physical risks are considerable, as they directly affect the asset values, operational capacities, and revenue streams of companies. Furthermore, these risks can disrupt global supply chains, leading to fluctuations in market prices and economic instability across sectors and regions (Zhang et al., 2017)

Transition Risks

Transition risks arise from the efforts to mitigate and adapt to climate change, including policy changes, technological shifts, market adaptations, and shifts in consumer preferences. These adjustments move economies towards low-carbon models, often taking the form of new policies like carbon taxes, regulatory changes, and shifts favouring sustainable practices and technologies (Bolton and Kacperczyk, 2021). The financial market's response to transition risks is complex, as these risks can lead to significant revaluation of assets and reallocation of capital. For example, in the long term, companies heavily reliant on fossil fuels or those with high carbon footprints may face increased costs, regulatory burdens, and reputational damage, leading to a depreciation in stock prices and investment returns (Pastor et al., 2021). In contrast, firms that proactively align with climate policies and invest in sustainable technologies can attract investor interest and see an increase in market valuation. This proactive adaptation and anticipation of policy and technological changes enable financial markets to incorporate these risks, showcasing a forward-looking approach essential to modern financial theory.

2.1 Climate Risk Pricing in Financial Markets

Both physical and transition risks are now recognized as factors that can influence the long-term sustainability and profitability of investments. The ability of financial markets to anticipate and react to these risks not only shapes investment portfolios but also plays a critical role in global efforts to combat climate change. Recognizing this, a comprehensive understanding of how these risks are integrated into asset pricing is essential for investors, policymakers, and stakeholders to make informed decisions that align financial goals with broader environmental objectives. However, understanding the dynamics and direction of these risks in the market remains complex. Empirical studies have demonstrated that climate-related risks are priced into financial markets, affecting both the valuations of equities and bonds. Central to this discussion are two concepts: the *brown premium* and the *greenium*.

The *brown premium* is grounded in the notion that companies with higher carbon emissions or those reliant on fossil fuels face more significant regulatory, operational, and reputational risks as the global economy transitions towards low-carbon alternatives. Bolton and Kacperczyk (2021) provide empirical evidence supporting the existence of a brown premium in their study, indicating that stocks of high-emission firms yield higher returns compared to their low-emission counterparts. Key drivers of the brown premium include the anticipation of stricter environmental regulations, carbon taxes, and emissions trading schemes, which can raise compliance costs for high-emission firms. As a result, this premium serves as compensation for investors facing the added risks linked to regulatory shifts and changing consumer preferences away from carbon-intensive products and services (Huynh and Xia, 2021). Additionally, the shift towards renewable energy and sustainable practices requires significant capital investments, which may not yield immediate returns. Increased awareness and activism around climate change can also damage the brand and market position of high-emission companies, affecting their long-term profitability (Pastor et al., 2021).

In contrast, the green premium, or *greenium*, reflects the premium investors are willing to pay for green investments, which are perceived as having lower risk profiles due to their alignment with sustainability trends and regulatory expectations. Alessi et al. (2021) explore the greenium phenomenon, demonstrating that green bonds and equities often trade at higher valuations and lower yields compared to their conventional counterparts. This premium arises from several factors, including the perception that green firms are better positioned to navigate the transition to a low-carbon economy, facing fewer regulatory and operational risks, and perceived as better hedges against climate policy risks (Pastor et al., 2022). Growing demand from institutional investors, such as pension funds and ESG-focused mutual funds, also drives up the prices of green assets. Moreover, investments in sustainable practices and technologies are associated with long-term value creation and resilience against climate-related disruptions (Alessi et al., 2021). Understanding the brown premium and greenium is necessary for investors and institutions aiming to optimize their portfolios by balancing risk and return in the context of climate change.

Theoretical frameworks such as the Intertemporal Capital Asset Pricing Model (ICAPM) (Merton, 1973) and factor models, like the Fama-French Factor Model (Fama and French, 2015), have been instrumental in explaining how climate risks influence asset pricing. ICAPM suggests that investors adjust their portfolios not only based on current risk-return profiles but also in anticipation of future risks, including those related to climate policies. By incorporating climate-related state variables, researchers have demonstrated how regulatory shifts and the transition to a low-carbon economy influence asset valuations and risk premiums (Ramadorai and Zeni, 2023). Furthermore, policy uncertainty related to climate change significantly affects asset pricing, with climate-policy-related risks consistently priced into the stock market, even when accounting for broader economic and political uncertainties (Pastor and Veronesi, 2013; Bali et al., 2017).

2.2 Importance and Relevance of Investigating Climate Risk Pricing

Investigating how climate risks are priced in the stock market is important for a number of related reasons. First, evaluating whether and how climate risks are embedded in stock prices is key to assessing market efficiency, which requires incorporating all available information, including climate-related risks, into asset prices (Bali et al., 2017). When these risks are factored in accurately, investors are able to develop portfolios that are more robust and risk management strategies that deal with climate-related uncertainties. Investors rely on such insights to optimize asset allocation, diversify risks, and implement hedging strategies against potential climate-induced financial volatility. Secondly, if the market underprices climate risks, investors may unknowingly expose their portfolios to higher-than-anticipated risks, especially in sectors like energy, agriculture, and insurance (Bolton and Kacperczyk, 2021). Conversely, overpricing these risks could reveal undervalued investment opportunities, promoting more strategic and sustainable investment practices. Additionally, understanding climate risk pricing can encourage the development of innovative financial products such as climate-linked bonds, green ETFs, or specialized climate risk funds. This knowledge is invaluable for policymakers and regulators seeking to enhance financial stability and sustainability. By comprehending how climate risks are reflected in stock valuations, investors, including institutional entities like pension funds, can effectively manage risk exposures, align portfolios with sustainability goals, and support financial stability (Bolton and Kacperczyk, 2021; Pastor et al., 2021).

2.3 Importance of Investigating Climate Risk Pricing in Sweden

Despite the expanding body of research on climate risk pricing in global financial markets, there remains a gap concerning the integration of these risks within Sweden's economic landscape. Sweden is internationally praised for its progressive environmental policies and commitment to sustainability. The Swedish government has set ambitious targets to achieve carbon neutrality by 2045, positioning itself ahead of many other nations (Swedish Climate Policy Council, 2024). The comprehensive climate policy framework, as outlined by the Ministry of Climate and Enterprise, emphasizes a robust transition towards a low-carbon economy through substantial investments in renewable energy, stringent environmental regulations, and incentives for green innovation (Government Offices of Sweden, 2021). Moreover, Sweden's proactive approach to integrating climate considerations into its financial system, highlighted by ambitious climate objectives, a robust legal framework, and the active engagement of financial institutions, serves as an model for other nations seeking to enhance the resilience of their financial markets to climate-related risks. These practices provide a strong foundation for further investigation into how effectively climate risks are currently priced within Swedish equities, an area my research aims to explore (Government Offices of Sweden, 2021; Swedish National Debt Office, 2020).

2.4 The Challenge of Measuring Climate Risks

While the integration of climate risks into financial markets has been increasingly acknowledged, accurately measuring these risks remains a challenge. The multifaceted nature of climate risks, which include both physical impacts and transition dynamics, complicates their quantification. These risks, marked by potential tipping points and unpredictability, pose significant challenges for traditional financial models, which often struggle to account for the evolving environmental, regulatory, and market conditions (Baranović et al., 2021). To address this, advances in textual analysis provide a promising approach and have been used by recent studies. By analyzing climate-related news articles and narratives, it is possible to construct proxies for both physical and transition risks that reflect the market's perception of these challenges. Importantly, this approach is reliable because the increase in news coverage typically corresponds directly to increases in the frequency or severity of climate events themselves, providing an accurate indicator of real-world events. The following chapter will examine the body of research on financial markets' integration of climate risk before outlining the method of textual analysis used in this study.

3 Literature Review

This section looks at three recent publications that build on one another, investigating whether climate risks are factored into asset pricing. By integrating macroeconomic viewpoints through textual analysis with advanced financial and microeconomic analyses, these studies demonstrate developing approaches connecting climate-related issues with investment decisions.

3.1 Earlier Studies on Climate Risk Integration in Asset Pricing

Firstly, Engle et al. (2020) develop a market-wide measure of climate risk by utilizing sophisticated textual analysis methodologies and testing it on U.S. equities. They construct a Climate Change Vocabulary (CCV) by applying a text-based analysis to authoritative climate documents, such as IPCC and IMF reports. Subsequently, they employ term frequency-inverse document frequency (TF–IDF) techniques on daily Wall Street Journal news articles, using the search phrase "climate change" to identify relevant news content. The daily climate change index is then formulated as the cosine similarity between the TF–IDF vectors of each day's news and the CCV. Employing the Fama-MacBeth regression framework, Engle et al. analyze the relationship between this climate risk index and asset returns by constructing portfolios transforming environmental scores (E-Scores) from firms' sustainability ratings and integrating them with market factors like size, value, and overall market exposure. These components are assigned weights based on their regression coefficients to manage risks tied to climate-related news effectively. The strategy focuses on capitalizing during moments when climate news has a significant impact on the market, helping to align portfolio returns with environmental risk exposures. The method developed in the study aggregates climate risk concern scores, demonstrating that hedge portfolios can account for up to 18.7% of the fluctuations in the Climate Change News Index.

Bua et al. (2022) build on Engle et al. (2020)'s research by analyzing the pricing of climate risks within European equity markets with the EuroStoxx 600 Index. In contrast to Engle et al. (2020), which did not differentiate between physical and transition risks, Bua et al. (2022) implemented a text-based approach to create separate indices for each risk type. Similarly, they developed vocabularies specific to each of the risk types by using IPCC reports, which allowed them to parse news articles for relevant content. By using cosine-similarity between the TF–IDF vector of the news document and the physical/transition risk document, they calculate the two risk indices, a Physical Risk Index (PRI) and a Transition Risk Index (TRI). This approach allowed for precise measurements of market responses to news about physical risks such as natural disasters, as well as transition risks, including policy shifts and technological advances aimed at climate change mitigation. To analyze how equity markets price these risks, they incorporated these indices into the Fama-French Five-Factor asset pricing model, enhancing the model's robustness in capturing the nuances of climate risk (Fama and French, 2015). Results indicate the presence of economically significant transition and physical risk premium, averaging 7.05% and 6.14% per year, respectively. These findings, emerging only after the critical 2015 threshold marked by the introduction of the Paris Agreement, provide first-time empirical evidence of climate-related risk pricing in European equity markets.

In a different approach, Faccini et al. (2023) examines whether climate risks from natural disasters, global warming, and policy changes are priced into U.S. stock markets using climate-change news from Reuters between 2000 and 2018, analyzed through Latent Dirichlet Allocation (LDA). In contrast to Engle et al. (2020) and Bua et al. (2022), this paper employs a narrower keyword-based approach, focusing exclusively on articles containing the terms' climate change' and 'global warming'. The LDA methodology facilitated the creation of factors that capture distinct dimensions of climate risk, specifically U.S. climate policy, international climate summits, natural disasters, and global warming. These factors were then used to construct portfolios based on stocks' sensitivities to these specific climate risks, and their performance was assessed using various asset pricing models, including the Fama-French Three-Factor, Carhart's Four-Factor, and the Fama-French Five-Factor Model (Fama and French, 1993, 2015; Carhart, 1997).

The analysis reveals a significant positive risk premium, specifically in the post-2012 period, with the monthly abnormal return ranging between 0.59% and 0.70%, which corresponds to an annual return of between 7.31% and 8.73%. This premium is closely linked to U.S. climate policy risks, intensifying after the start of Barack Obama's second presidential term, which was marked by a stronger focus on sustainability and environmental policies. The year 2012 marked a critical turning point where financial markets began to prioritize the risks from governmental interventions in climate policy, demonstrating heightened responsiveness to policy changes over direct physical impacts of climate change. Results shows that stocks with higher climate betas, reflecting a positive sensitivity to climate policy, generally yield higher returns. This underscores a risk premium associated with stocks that are better aligned with green policies or are more proactive in their environmental strategies, highlighting the financial benefits of aligning with new climate policies.

3.2 Choice of Methodology

Drawing inspiration from the methodologies used in the works of Faccini et al. (2023), Engle et al. (2020), and Bua et al. (2022), this research employs advanced textual analysis techniques tailored to the unique characteristics of Sweden's financial market and regulatory environment. Specifically, the study utilizes TF-IDF to identify relevant keywords for searching news articles and LDA to derive topics from the collected text, which are then used to create factors capturing various dimensions of climate risk. This approach aims to provide a deeper understanding of how climate risks fit into asset pricing, offering insights for investors and firms in Sweden and potentially extending to other markets with similar characteristics. The next chapter will go into greater detail about the creation of the textual climate risk factors aimed at quantifying the impact of climate-related discussions in news articles.

4 Methodology for Textual Analysis of Climate Risk News

Textual analysis has proven to be a practical way of measuring the influence of climate-related discussions on financial markets. This chapter goes through the methodology behind how climate-related news articles are transformed into measurable indicators for empirical analysis. It begins with an overview of Natural Language Processing (NLP) and text-mining methods. Next, it details the lexical approach used to build vocabularies for transition and physical risks, followed by a description of the data sources and criteria for selecting Swedish news articles. Finally, it introduces a semantic method, which uncovers the main topics in the corpus and the creation of the climate risk factors. For a detailed definition of key NLP and LDA terminology used throughout this analysis, see Table A1.

4.1 Natural Language Processing and Text Mining Methodologies

NLP utilize artificial intelligence and statistical machine learning, blending computational linguistics with applied mathematics. This field has evolved to develop sophisticated techniques for mining and interpreting vast quantities of unstructured text data. In economic and financial research, the innovative application of NLP has shown how textual data can be systematically transformed into actionable economic insights (Manning and Schütze, 1999).

As Gentzkow et al. (2019) describes, the foundation of statistical text analysis lies in transforming a text corpus $\mathbf{D}$, composed of individual documents $\mathbf{d}$, into a numerical array $\mathbf{C}$. Each row $\mathbf{c}_d$ in this array represents a single observation $\mathbf{d}$ (i.e., a document) and is expressed as a numerical vector derived from the frequency or presence of predefined tokens. Tokens typically represent individual words or terms, and their aggregated counts in a document form what is known as the term-frequency vector. The frequency of a specific term $\mathbf{n}$ in a document $\mathbf{d}$ is denoted by $\mathrm{tf}(\mathbf{d})_{\mathbf{n}}$. This process of converting text data into numerical data enables the application of machine learning algorithms, which typically require numeric input. The term frequencies help define a vector space $V : \mathbf{d} \to \mathbb{R}^{\dim(\mathbf{N})}$, where the dimension $\mathbf{N}$ is determined by the total number of unique terms in the corpus. Due to the typically large size of $\mathbf{N}$, text data is transformed into a high-dimensional space $\mathbb{R}^{\dim(\mathbf{N})}$, presenting significant computational challenges.

To manage these challenges and enhance computational efficiency, it is necessary to reduce the dimensionality of $\mathbf{N}$, that is, the number of tokens considered, through established preprocessing techniques. These techniques include removing rare words, applying stemming and lemmatization to reduce words to their base forms, and other methods to simplify the data without losing crucial information. These steps are important in preparing text data for predictive modelling and are detailed further in Appendix A. Subsequently, the numerical array $\mathbf{C}$ is employed to predict values $\hat{\mathbf{V}}$ of unknown outcomes $\mathbf{V}$ using statistical methods. This transition from qualitative text to quantitative analysis enables the application of a range of machine learning models to infer patterns, trends, or outcomes based on the content of the text data. These methods are commonly grouped according to the level at which they process text:

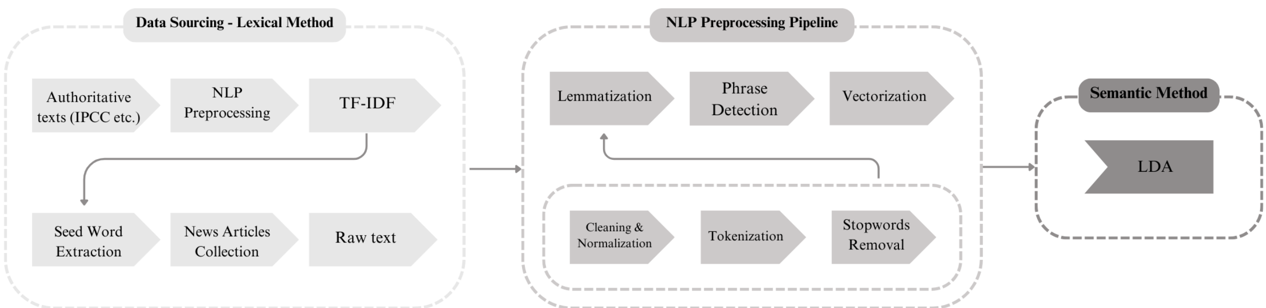
Lexical or Dictionary Methods: Operating primarily at the word level, these methods focus on the occurrence or frequency of tokens within a corpus, quantifying aspects such as sentiment, topic prevalence, or thematic emphasis by analyzing term appearances. This approach is beneficial for capturing straightforward information from specific keywords or phrases that are associated with particular concepts or sentiments.

Syntactic Methods: These methods analyze the ordered sequences of tokens within sentences, taking into account grammatical structures and the relationships between words. This approach enables the extraction of nuanced information, such as the identification of specific sentence structures or patterns that can indicate underlying economic sentiments or trends. By focusing on sentence-level structures, syntactic analysis can provide insights beyond mere word frequency.

Semantic Methods: Investigating context-level meaning, these methods investigate the meaning conveyed by tokens, often through their co-occurrences with other terms, to understand the context and semantic relationships. Semantic analysis facilitates a more profound comprehension of text, enabling the extraction of implied sentiments, thematic connections, and conceptual linkages that are not immediately obvious through lexical or syntactic analysis alone.

NLP is an effective tool for investigating causal relationships in economic and financial research in addition to producing accurate and frequent predictions, there techniques such as *term frequency-inverse document frequency* (TF–IDF) and *Latent Dirichlet Allocation* (LDA) are great in extracting meaningful patterns from large-scale textual data. By employing both lexical and semantic methods, this research moves beyond simple predictive models to establish a robust framework for analyzing climate risks, thereby enhancing the analysis of economic trends and financial market behaviours. For a detailed illustration of the NLP process used in this study, see Figure 1 below.

Figure 1: Flowchart of NLP and Text Mining Methods



Note: The NLP preprocessing steps described apply to both the authoritative documents and the news articles. However, different language-processing tools are used depending on whether the text is in English or Swedish. "NLP Preprocessing Pipeline" illustrates these steps in more detail, outlining the specific tasks (such as cleaning, tokenization, and lemmatization) that are carried out.

4.2 Lexical Method

Building on the NLP methodologies discussed, this section outlines the approach used to identify and extract seed words related to climate risk from news articles, which serve as the foundation for differentiating between transition and physical risks associated with climate change. This process draws on the analytical techniques presented in Engle et al. (2020) and Bua et al. (2022), utilizing TF–IDF weighting to quantify the relevance of climate-related terms in textual data and employing authoritative sources to extract corpora (document collections) for transition and physical risks. This methodology systematically captures the prevalence of key terms in news articles, enabling the creation of robust climate risk indexes.

Construction of Transition and Physical Risk Corpora

The initial phase involves the extraction of a list of *Seed Words*, ($\mathcal{S}_t$) for transition risk and ($\mathcal{S}_p$) for physical risk. An extensive collection of authoritative climate change texts is compiled, predominantly featuring reports from the Intergovernmental Panel on Climate Change (IPCC), Swedish Government climate policy documents, and other esteemed publications. These sources are carefully chosen and reviewed to cover a broad spectrum of climate risk facets relevant to Sweden. The complete list of these sources, including titles, years, and their relevance to the respective risk categories, is provided in Table A2.

TF–IDF weighting scheme quantifies the importance of a word within documents relative to a corpus. By applying the TF–IDF metric to the authoritative texts, each term is assigned a weight reflecting its relative importance to transition and physical risk topics. This approach ensures a rigorous, data-driven selection of terms, mitigating the influence of subjective bias in the analysis. The detailed formulation of TF–IDF is provided below:

$$\text{tf-idf}(t,d) = \text{tf}(t,d) \times \text{idf}(t)$$

Here, $\text{tf}(t,d)$ represents the frequency of term t in document d. It is computed by dividing the number of occurrences of the term t in document d ($n_{t,d}$) by the total number of terms in document d ($\sum_{t' \in d} n_{t',d}$):

$$\text{tf}(t,d) = \frac{n_{t,d}}{\sum_{t' \in d} n_{t',d}}$$

The inverse document frequency ($\text{idf}(t)$) of the term t quantifies the inverse of how frequently the term appears across the corpus D, thereby increasing the importance of rarer terms. This is formulated as:

$$\text{idf}(t) = \log\left(\frac{N}{1+n_t}\right)$$

Where N is the total number of documents in the corpus, and n_t represents the number of documents that contain the term t. This function serves to amplify the significance of terms that are infrequent across the corpus.

From the TF–IDF analysis, the 50 most relevant terms per category are extracted to form the two lists of seed words for Transition Risk ($\mathcal{S}_t$) and Physical Risk ($\mathcal{S}_p$). For Transition Risk ($\mathcal{S}_t$), some of the key words include {*klimatförändring* (climate change), *koldioxid* (carbon dioxide), *förnybar energi* (renewable energy), *hållbar utveckling* (sustainable development), *utsläppsminskning* (emission reduction), *grön teknik* (green technology)}, while for Physical Risk ($\mathcal{S}_p$), the seed words includes terms such as {*översvämning* (flood), *torka* (drought), *skogsbrand* (forest fire), *extremväder* (extreme weather), *havsnivåhöjning* (sea-level rise), *värmebölja* (heatwave)}. These tokens capture key concepts related to transition and physical risks, providing a basis for analyzing climate risk discussions in news articles. The full list of seed words can be found in Table A3.

4.3 Textual Data Sourcing

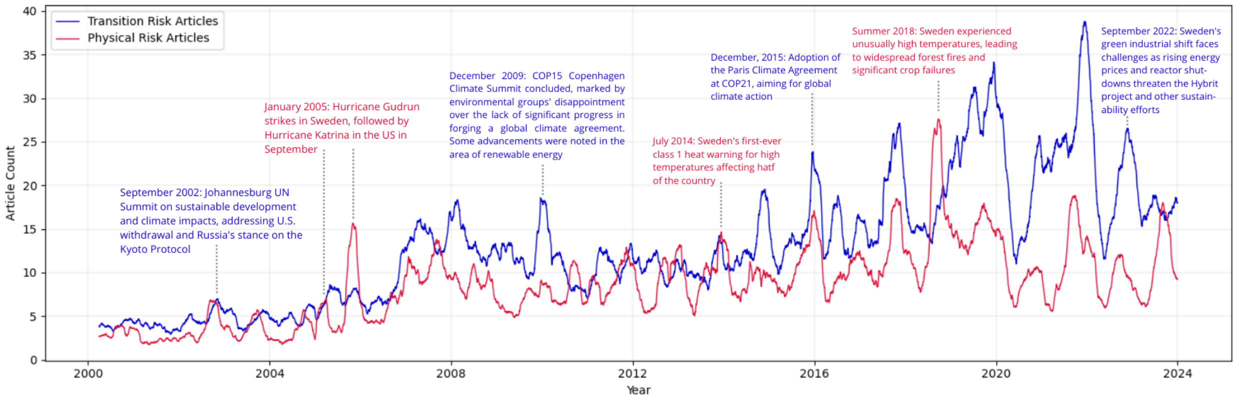
By using the extracted terms from the TF-IDF analysis, these will guide in finding the news articles necessary for building the climate risk factors in Sweden. The factors are based on articles published between January 1, 2000, and December 31, 2023, sourced from prominent Swedish publishers: 'Aftonbladet', 'Dagens Industri', 'Dagens Nyheter', 'Expressen' and 'Svenska Dagbladet'. These publishers were selected because of their wide national reach and substantial readership, which ensures an accurate representation of Sweden's discussion on the mentioned climate risks.

National media outlets are presumed to have a greater influence on public and policymakers' perceptions, as they cover significant events and policy shifts related to climate change, environmental impacts, and sustainability efforts. While regional news can impact local audiences, national media are more likely to report events with broad repercussions, shaping nationwide policies and opinions. Yet, if a regional event holds enough significance to affect national policies or perceptions, it is likely to be covered by national media, thus being captured in the dataset. Therefore, focusing on these national publishers guarantees that the analysis captures the most impactful climate-related news, representative of the information consumed by the majority of the population.

The articles for this analysis were sourced from the Swedish media archive Retriever, which maintains a comprehensive database of published news. To extract articles, a search query was employed using the string *"klimatförändring* OR extremväd* OR förnybar AND energi"*, where the asterisk (*) functions as a wildcard, capturing various extensions of the root words to include a broad spectrum of related discussions on climate change and its mitigation.

After processing and filtering, the data shows a total of 113,974 articles and 24528 unique words associated with Transition risk; 75,286 articles, and 15993 unique words categorized under Physical risk. For a more detailed description of the filtering processes used in this study, please see Appendix A. The distribution of these articles over time can be seen in the graph provided in Figure 2.

Figure 2: Trends in Transition and Physical Risk Article Corpora (2000-2024)



Note: The graph displays rolling means over a 3-month window to smooth variations in the monthly data.

Upon conducting a similarity analysis between the Transition risk and Physical risk article corpora, 86.25% of the information within the Transition risk dataset and 79.39% of the information within the Physical risk dataset represent unique content, ensuring a substantial separation between the two collections. Specifically, only 13.75% of articles in the Transition risk dataset overlap with the Physical risk, and 20.61% in the Physical risk dataset overlap with the Transition risk. This distribution corresponds with the findings of Bua et al. (2022), highlighting a similar pattern of thematic overlap in their study. Given the inherent interconnectedness of the topics covered in both datasets, such as overlapping themes or shared sources, a certain degree of overlap is anticipated. For example, news stories on climate change typically cover multiple aspects, often relevant to both datasets. A notable example is the Paris Climate Conference in December 2015, where the Paris Agreement was adopted, featured in both datasets.

Periods of heightened climate-related news coverage reveal distinct surges in both physical and transition risks. To mention some when reviewing these surges: In June and July 2017, China and the European Union's commitments to the Paris Agreement, alongside the Trump Administration's announced withdrawal from the agreement, and the G20 summit in Hamburg emphasizing climate transition strategies marked key moments in international climate policy. From mid-2018 to June 2020, developments such as Denmark's Baltic Pipe project aimed at reducing European dependency on Russian gas and the European Central Bank's investments in fossil fuel bonds highlighted the tension between traditional energy reliance and sustainable transition. These events coincided with the European Union's Climate Strategy for 2050, which sought climate neutrality through substantial renewable investments. In December 2021 and August 2023, media coverage surged due to severe physical climate events, including Supertyphoon Rai in the Philippines, Storm Helga in southern Sweden, and extreme weather events in Alaska and Hawaii. Additionally, Russia's invasion of Ukraine in February 2022 significantly impacted European energy policies, prompting Germany to increase coal usage and causing rising electricity prices in Sweden. Concurrently, Sweden's debates over nuclear power and renewable energy investments received prominent media attention. Throughout this period, Greta Thunberg's sustained climate activism, starting in 2018, has significantly influenced public and political discourse.

These surges are reflected in a wide variety of articles discussing everything from immediate environmental impacts to long-term policy changes. To better understand these thematic structures, a systematic analysis of the latent thematic components within these articles over time is essential, as detailed in the following section.

4.4 Semantic Method

In the previous section, selected keywords were employed to identify climate risk-related articles by analyzing the relative frequency of these terms over time. Building on the methodologies presented by Faccini et al. (2023), this section aims to uncover latent narratives from the constructed *corpora* by examining the semantic structure of the articles and extracting specific topics. By applying semantic analysis techniques similar to those used by Faccini et al. (2023), this research identifies underlying themes and discourse patterns related to climate risks. These extracted topics will serve as factors, providing a detailed framework for analyzing climate risk discussions and their implications for asset pricing in the Swedish equity market.

Firstly, topics within articles are identified using LDA. These topics aim to approximate the broader and more nuanced concept of narratives. LDA is chosen because it jointly captures the latent structure within each document and the broader themes spanning the entire corpus, thereby overcoming many of the limitations found in earlier methods for latent text classification (Blei, 2012). The outlined procedure allows for the identification of topics related to transition and physical climate risks and distinguishes them from other less relevant topics. Before beginning the process, the LDA algorithm requires further preprocessing of the tokenized articles to reduce the dimensionality of the corpus. The steps undertaken are detailed in Appendix A.

4.5 Latent Dirichlet Allocation

Initially proposed by Blei et al. (2003) and expanded upon by Blei (2012), LDA is an effective tool for uncovering underlying patterns in highly heterogeneous data. It is particularly useful in the domain of topic discovery within documents, as it can handle the complex relationships between words in the text. LDA is commonly recognized as a form of probabilistic topic modelling and is classified under generative probabilistic models. The generative process defines a joint probability distribution over observed variables (the words in the corpus) and latent variables (topics and topic proportions). Probabilistic modelling uses this joint distribution to infer the conditional distribution of the latent topics given the observed words, also known as the posterior distribution. Building on the generative process, the algorithm estimates these distributions by calculating the posterior probabilities of the latent variables. A more detailed explanation of the inference process is provided in Appendix A. For LDA, the key assumptions are that each document is a mixture of topics and that each topic is a probability distribution over words. The words in a document are generated by first sampling a topic from the document's topic distribution and then sampling a word from that topic's word distribution. Formally, the model is defined as follows:

Let V be the size of the article vocabulary (the total number of unique words in the corpus after text processing) and D the number of documents. The model assumes a fixed number of topics, denoted by K. Each topic k ($k = 1, 2, \ldots, K$) is associated with a multinomial distribution over the vocabulary, represented by $\phi_k = (\phi_{k,1}, \phi_{k,2}, \ldots, \phi_{k,V})$, where $\phi_{k,w} = p(w \mid k)$ is the probability of word w given topic k. A multinomial distribution is a generalization of the binomial distribution to multiple categories, allowing for the assignment of probabilities to each word in the vocabulary. In this context, it models the likelihood of each word's occurrence within a specific topic, effectively capturing the distribution of words that characterize each topic.

Similarly, each document d $(d = 1, 2, \ldots, D)$ has a multinomial distribution over topics, denoted by $\theta_d = (\theta_{d,1}, \theta_{d,2}, \ldots, \theta_{d,K})$, where $\theta_{d,k} = p(k \mid d)$ represents the probability of topic k in document d. For each word position n in document d (where $n = 1, 2, \ldots, N_d$, and N_d is the number of words in document d), the generative process is as follows:

A topic assignment $z_{d,n}$ is drawn from the multinomial distribution over topics θ_d. Given the topic assignment $z_{d,n}$, the observed word $w_{d,n}$ is drawn from the multinomial distribution over words for topic $z_{d,n}$:

$$z_{d,n} \sim \text{Multinomial}(\theta_d), \quad w_{d,n} \sim \text{Multinomial}(\phi_{z_{d,n}}).$$

The multinomial distributions over topics θ_d and over words ϕ_k are themselves drawn from Dirichlet priors with hyperparameters α and β, respectively:

$$\theta_d \sim \text{Dirichlet}(\alpha), \quad \phi_k \sim \text{Dirichlet}(\beta).$$

The Dirichlet distribution, defined by α and β, serves as a flexible method for modelling the variability and sparsity in topic compositions across documents and word distributions within topics. It ensures that each document can exhibit a unique mixture of topics, and each topic can contain a distinctive blend of words, reflecting the natural diversity found in real-world text data. A smaller α leads to sparser topic distributions in documents, implying that each document is likely composed of fewer topics. Similarly, a smaller β results in topics being characterized by a few high-probability words. This is further explained in Appendix A.

In this analysis, α is set to 0.01, a small value that encourages sparse topic distributions over documents. This choice is justified by the nature of news articles, which often focus on specific subjects, thereby enhancing the model's ability to assign high probabilities to the most relevant topics within each document. For the word distribution hyperparameter, β is set to 0.001, promoting sparse word distributions over topics and resulting in topics characterized by a few high-probability words. This contributes in creating distinct and interpretable topics. Selecting the optimal number of topics K is a critical step. Since the true number of topics is unknown, a data-driven approach is employed to determine K. Following the method proposed by Faccini et al. (2023), the perplexity and coherence score on a held-out validation set is compared for different values of K. The procedure, detailed in Appendix A, suggests an optimal number of topics $K_{\text{opt}} = 20$[1].

[1] Faccini et al. (2023) followed Heinrich (2009) approach by setting $\alpha = \frac{1}{K}$ and $\beta = \frac{1}{10}$. They also utilized the CV coherence score measure by Röder et al. (2015) to determine the optimal number of topics, ultimately selecting a model with 25 topics. In contrast, this study employed a grid search using a random sample of 10,000 articles to refine the estimates for α, β, and amount of topics K, more precisely.

The joint probability of the observed words $\boldsymbol{w} = \{w_{d,n}\}$ and the latent variables $\boldsymbol{z} = \{z_{d,n}\}$, along with the topic distributions $\boldsymbol{\theta} = \{\theta_d\}$ and word distributions $\boldsymbol{\phi} = \{\phi_k\}$, is then given by:

$$p(\boldsymbol{w}, \boldsymbol{z}, \boldsymbol{\theta}, \boldsymbol{\phi} \mid \alpha, \beta) = \left(\prod_{k=1}^{K} p(\phi_k \mid \beta) \right) \left(\prod_{d=1}^{D} p(\theta_d \mid \alpha) \prod_{n=1}^{N_d} p(z_{d,n} \mid \theta_d) p(w_{d,n} \mid \phi_{z_{d,n}}) \right) \tag{1}$$

Where:

- $p(\phi_k \mid \beta)$ is the Dirichlet prior over the word distribution for topic k, specifying initial assumptions about the distribution of words within each topic.
- $p(\theta_d \mid \alpha)$ is the Dirichlet prior over the topic distribution for document d, encoding initial assumptions about how topics are distributed within each document.
- $p(w_{d,n} \mid \phi_{z_{d,n}}) = \phi_{z_{d,n}, w_{d,n}}$ is the probability of word $w_{d,n}$ appearing in topic $z_{d,n}$, indicating the strength of association between words and topics.
- $p(z_{d,n} \mid \theta_d) = \theta_{d, z_{d,n}}$ is the probability of topic $z_{d,n}$ appearing in document d, reflecting the prevalence of topics within the document.

Thus, LDA works by uncovering the hidden topic structure within a collection of documents. Each topic is represented as a probability distribution over words (ϕ_k), while each document is characterized by a probability distribution over topics (θ_d).

4.6 Selection and Interpretation of Topics

Given the extensive range of topics generated from the LDA, a systematic approach is essential to select the most relevant ones for further study. To effectively manage this vast array of topics, I established three primary criteria for selection:

(1) Clear Interpretation: Topics chosen must contain words that clearly capture either physical risks or transition risks. The selection process is supported by a detailed analysis of topic coherence and prevalence, as described in Appendix A. *(2) Broad Market Relevance:* The topics must have a wide-reaching impact on the Swedish market, addressing systemic issues that could influence market-wide asset pricing. This ensures that the selected topics are not overly niche, allowing for a more comprehensive analysis of climate risks. *(3) Categorical Relevance:* The topics should be strictly aligned with the categories they represent, either transition or physical risks. The goal is to ensure that each topic is contextually appropriate and specifically tailored to the corresponding risk category, enabling precise and effective analysis of how these risks are portrayed in Swedish media and their potential impacts on asset valuations. All topics created are presented and detailed in Table A5 and Table A6.

Applying these criteria resulted in the selection of four key topics for analysis, presented in Figure 3. Topics 3, 12, and 13 were chosen from the Transition risk category. Topic 3, Swedish Climate Policies, consists of governmental initiatives aimed at reducing emissions and promoting sustainable practices within Sweden, providing insight into national policy impacts on climate transition. Topic 12, Energy Transition Policies, focuses on the shift towards renewable energy sources and associated policy frameworks around energy. Topic 13, International Climate Agreements, captures global efforts and international collaborations aimed at mitigating climate change. From the Physical risk category, Topic 16, Global Warming, was selected for its focus on chronic physical climate risk. This topic addresses rising temperatures, extreme weather events, and their consequent effects on ecosystems and human activities, making it a critical factor for evaluating physical climate risks. Topic 0 was initially considered because it directly addresses acute risks, such as floods, hurricanes, and droughts. However, it was ultimately excluded from the final selection due to its broad and general nature, covering a wide range of weather-related events. Including Topic 0 would have introduced thematic dilution, overshadowing more targeted topics and reducing the precision and clarity of the study's findings.

Figure 3: Distribution of Climate Risk Topics Identified by the LDA Analysis

(a) Swedish Climate Policies (b) Energy Transition Policies (c) International Climate Agreements (d) Global Warming

4.7 Quantifying and Visualizing LDA-Based Climate Factors

For each news article within the dataset, the estimated topic share is determined as the proportion of words associated with a given topic relative to the article's total word count. On days when multiple articles are published, the risk measure for each topic is calculated by normalizing the sum of the topic shares from all articles of that day. This method ensures that the measurements account for the overall news volume, providing a balanced view of each topic's relative importance on any given day. The normalized risk measure $R_{i,t}$ for the i-th topic on day t is given by:

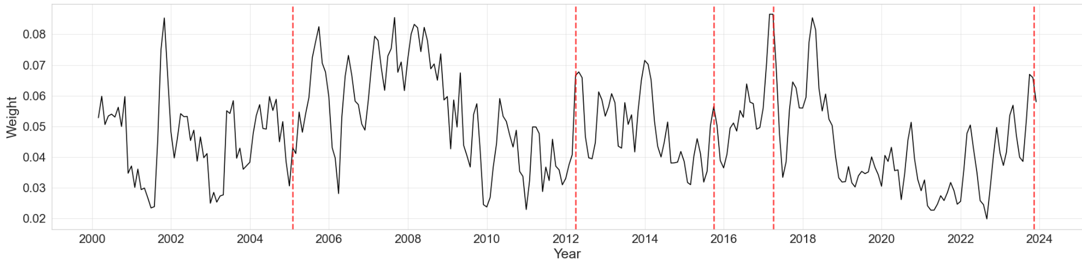
$$R_{i,t} = \frac{\sum_{d \in t} \theta_{d,i}}{N_t} \tag{2}$$

Where:

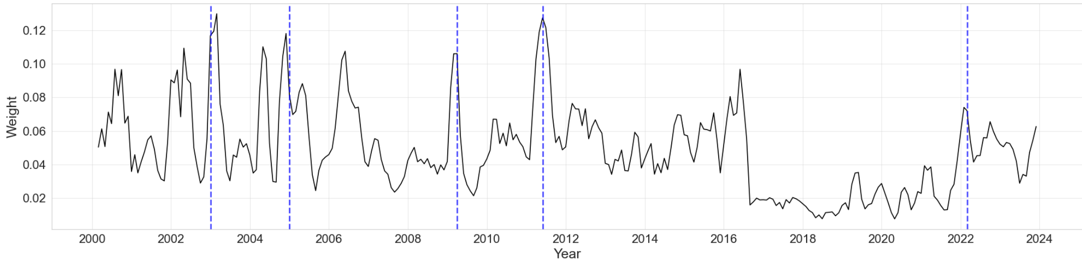
- $\theta_{d,i}$ is the topic share of the i-th topic in article d,
- N_t is the total number of articles published on day t.

By dividing by the total number of articles each day, N_t, the calculation adjusts for daily fluctuations in news output, which might otherwise bias the perceived importance of the topics. The volume-weighted approach is crucial for capturing both the quantity and the focus of news coverage, reflecting the dynamic nature of media attention. It provides a nuanced view of the information landscape, ensuring the study's analysis remains robust and reliable. Moreover, variations in news volume between corpora on physical and transition risks could lead to imbalances in analysis. For instance, the transition corpus consistently contains more articles, and it might appear that transition risks are more urgent or critical. Additionally, an overall increase in news volume could be mistakenly interpreted as a rise in risk severity. Normalization by N_t mitigates these issues, ensuring that data comparisons and conclusions are based on proportionate topic coverage. On the following page, the results illustrating trends over time for the four identified climate factors are presented in Figure 4.

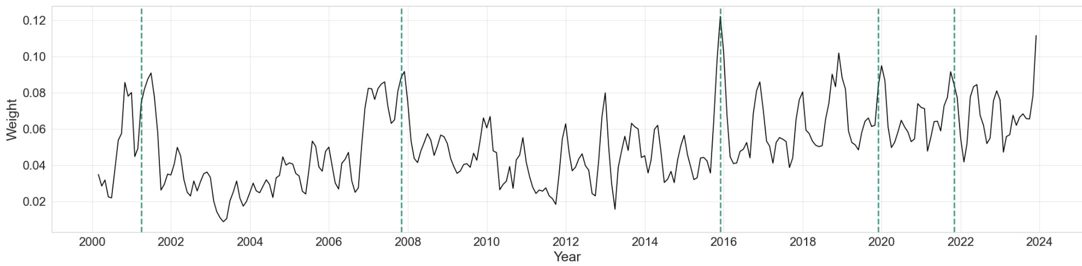
Figure 4: Trends of Identified Climate Risk Topics from LDA Analysis



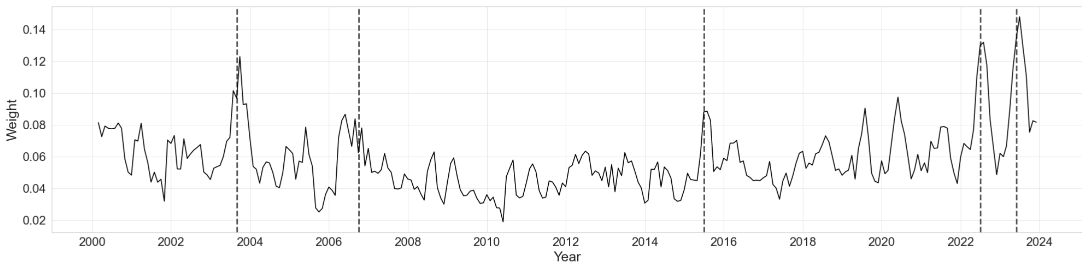
(a) Swedish Climate Policies Textual Factor: Feb 2005: Kyoto Protocol into force, committing Sweden to emission reductions; Apr 2012: Sweden achieved 50% renewable energy usage and announced its goal of No Fossil Fuel Energy by 2050; Oct 2015: Initiated Fossil Free Sweden, aiming to eliminate fossil fuel dependence; May 2017: Swedish Climate Act passed, legally binding climate goals; Nov 2023: The second climate policy action plan was announced, outlining further climate initiatives.



(b) Energy Transition Policies Textual Factor: Jan 2003: EU Renewable Energy Directive negotiations begin, setting renewable targets; Feb 2005: EU Emissions Trading Scheme (EU ETS) established, creating a carbon market; Apr 2009: Adoption of the EU Renewable Energy Directive, establishing binding renewable energy targets across Europe to achieve a 20% share from renewables by 2020; Jun 2011: German Nuclear Phase-Out Decision, influencing European energy policies; Mar 2022: Russia invades Ukraine, impacting energy security and policies.



(c) International Climate Agreements Textual Factor: Mar 2001: US announces withdrawal from Kyoto Protocol, affecting global commitments; Nov 2007: Bali Climate Change Conference (COP 13); Dec 2015: Paris Climate Change Conference (COP 21); Dec 2019: Madrid Climate Change Conference (COP 25); Nov 2021: Glasgow Climate Change Conference (COP 26).



(d) Global Warming Textual Factor: Sep 2003: European Heatwave (France), a severe event that led to extreme temperatures and resulted in over 15,000 deaths; Oct 2006: Stern Review on Economics of Climate Change, emphasizing economic impacts; Jul 2015: Record Heat in Sweden, part of broader European heatwave trends; Jul 2022: European Heatwave and Wildfires; Jun 2023: Record Global Temperature and Ongoing Heatwaves.

Note: Climate textual factors from January 1st, 2000 to December 31st, 2023. The Y-axis represents the topic share percentage (weight) for each factor, indicating the proportion of words in each article associated with a specific climate risk topic. Topic shares are aggregated daily and then averaged over a 3-month rolling window to smooth out short-term fluctuations.

5 Methodology for Asset Pricing and Financial Data

Having completed the textual analysis and created the climate risk factors, we now turn our focus to the financial data and asset pricing methodologies that will be used to explore whether these risks are reflected in the Swedish equity market. The Fama-French model, a key component of modern asset pricing theory, is central to this analysis.

The Fama-French models are primarily structured as time series regression models grounded in portfolio theory. These models extend the traditional Capital Asset Pricing Model (CAPM) by incorporating additional factors that capture a broader spectrum of stock return variations (Fama and French, 1993; Sharpe, 1964; Lintner, 1965). The Fama-French framework offers more flexibility, allowing for the integration of further factors that capture other relevant dimensions of risk, which has inspired the creation of several model versions. The primary objective of a Fama-French model is to extract multiple sources of systematic risk that influence asset returns. By doing so, it seeks to explain the cross-sectional differences in expected returns. The model achieves this through factor loadings, where each factor represents a distinct dimension of risk that systematically affects returns across different assets. This multifactor approach allows for a more nuanced assessment of asset performance, accounting for complexities and anomalies that CAPM cannot address (Fama and French, 1993). These extensions continuously improve the accuracy of asset pricing methodologies, making the Fama-French approach a superior tool for both academic research and practical investment strategies. In this study, three different Fama-French models will be employed to ensure robustness in analyzing capital asset returns. These models will be thoroughly discussed in the subsequent section alongside the data utilized.

5.1 The Fama-French Three Factor Model (FF3)

Unlike the CAPM framework, which solely relies on the market risk premium to explain asset returns, the Fama-French Three-Factor Model (FF3) introduces two additional factors, Size (SMB, Small Minus Big) and Value (HML, High Minus Low), to account for anomalies in asset returns that CAPM fails to explain. These factors are designed to capture the excess returns associated with small-cap versus large-cap stocks and high book-to-market versus low book-to-market stocks, respectively. This multifactor model addresses empirical anomalies such as the size effect, where smaller firms tend to outperform larger ones, and the value premium, which sees high book-to-market firms outperforming those with lower ratios (Fama and French, 1993).

The FF3 model is expressed as:

$$r_{it} - r_{ft} = \alpha_i + \beta_{1i}(r_{mt} - r_{ft}) + \beta_{2i}\mathrm{SMB}_t + \beta_{3i}\mathrm{HML}_t + \epsilon_{it} \tag{3}$$

Where:

- r_{it} = Return of the i^{th} asset or portfolio at time t,
- r_{ft} = Risk-free rate at time t,
- r_{mt} = Return of the market portfolio at time t,

- $r_{mt} - r_{ft}$ = Market risk premium (Mkt-Rf), the excess market return over the risk-free rate,
- α_i = Intercept, indicating the abnormal returns of the i^{th} asset,
- β_{1i} = Sensitivity of the asset returns to market movements, measured by the market risk premium,
- β_{2i} *SMB (Small Minus Big)* = Excess returns of small-cap over large-cap firms,
- β_{3i} *HML (High Minus Low)* = Excess returns of high over low book-to-market firms,
- ϵ_{it} = Error term capturing the idiosyncratic risk.

Portfolios are constructed based on size and book-to-market ratios to calculate the SMB and HML factors, thereby capturing the excess returns associated with these dimensions. These portfolios form the empirical basis for the calculations, directly influencing the regression coefficients that measure the size and value effects on asset returns. A detailed guide on how these portfolios are systematically constructed for all asset pricing models is provided in Appendix B.

5.2 The Fama-French-Carhart Model (FF4)

Building on the Fama-French Three-Factor Model, the Fama-French-Carhart Four-Factor Model introduces a momentum factor, referred to as β_{4i} *Momentum* (MOM), which captures the persistence of stock returns. This factor measures the tendency for assets that have performed well in the past to continue performing well in the short term, reflecting the excess return of past winners over past losers. It is quantitatively defined by the difference between the average returns of high-momentum portfolios (winners) and low-momentum portfolios (losers) (Jegadeesh and Titman, 1993; Carhart, 1997). For simplicity, this model is referred to as the Four-Factor Model in this study, indicating its extension of the original model.

5.3 The Fama-French Five Factor Model (FF5)

The Fama-French Five Factor Model extends the FF3 by adding two more beta coefficients: β_{4i} *Profitability* (RMW) and β_{5i} *Investment* (CMA), addressing criticisms related to the omission of these dimensions in earlier models (Fama and French, 2015). These factors aim to capture variations in returns that are associated with firm-specific characteristics of profitability and investment patterns. The factor *RMW (Robust Minus Weak)* represents the return differential between firms with robust and weak profitability. It is calculated as the average return on firms with high operating profitability minus the average return on firms with low operating profitability, thereby providing insight into the profitability dimension of asset returns (Fama and French, 2015). *CMA (Conservative Minus Aggressive)* measures the return differential between firms that employ conservative versus aggressive investment strategies. This factor is calculated by subtracting the average return on aggressive investment firms from the average return on conservative investment firms, reflecting the investment behaviour of firms (Fama and French, 2015).

5.4 Data Extraction

To accurately construct factors for the Swedish equity market as outlined in the Fama-French and Carhart models, this study utilizes a dataset of stocks listed on the Stockholm Stock Exchange (SSE) from January 1, 2000, to December 31, 2023. This dataset includes financial and market data for 479 firms listed in the OMX Stockholm All-Share Index (OMXPI).[2] The OMXPI offers a broad representation across various sectors, providing a solid basis for analyzing market behaviours and trends. Due to the dynamic nature of the stock market, characterized by companies being listed, delisted, merging, or going bankrupt, the dataset reflects these ongoing changes and is unbalanced by nature. The Fama-French model's portfolio construction methodology and its extensions specifically account for these dynamics, ensuring robust empirical analysis despite fluctuations in the number of firms over time (Fama and French, 1993, 2015; Carhart, 1997). Detailed data cleaning and preparation procedures are outlined in Appendix B.

Financial Variables:

For each company, the following key financial and market variables were collected daily:

- *Adjusted Closing Price*: Reflects stock prices accounting for corporate actions (e.g., stock splits, dividends). Used to calculate returns, which serve as the basis for factors such as size, value, and momentum.
- *Number of Shares Outstanding*: Used to calculate market capitalization, fundamental for constructing the size-based factor.
- *Book Value per Share*: Essential for computing book equity and the book-to-market ratio, a key input for the value factor.
- *Total Assets*: The sum of all assets owned by a firm, including cash, property, and equipment. Used to determine asset growth and required for determining the investment factor.
- *Operating Expenses*: All costs related to the day-to-day functions of a business, excluding the cost of goods sold (COGS) and used in calculating operating profitability.
- *Net Revenues*: Total income generated from sales of goods or services and also used in calculating operating profitability.

Market Index and Risk-Free Rate:

The market return is proxied by OMXPI, which is a value-weighted index that includes all stocks listed on the SSE. The use of a value-weighted index aligns with previous research and ensures that the market proxy captures the overall performance of the Swedish equity market (Fama and French, 1993, 2015). The risk-free rate is represented by the one-month Swedish Treasury bill rate obtained from the Central Bank of Sweden (Sveriges Riksbank).[3] This choice is consistent with prior studies in the Swedish context (Aytug et al., 2020), reflecting the return on a risk-free investment in the domestic market. A full list of financial variable descriptions and sources is provided in Table B1.

[2] Data retrieved from Refinitiv Eikon.
[3] Swedish Treasury bill rate data retrieved from Sveriges Riksbank.

5.5 Factor Independence and Correlation Metrics

Before proceeding with asset pricing tests, it is important to verify that the climate risk factors developed are robust and independent. By examining the pairwise correlations between the climate textual factors, traditional Fama-French equity factors, and key macroeconomic indicators, I assess the reliability and relevance of the newly created factors as potential explanatory variables in asset pricing. The correlation analysis includes macroeconomic indicators such as the Economic Policy Uncertainty Index (EPU) and the Yield Curve, which are widely recognized for their effectiveness in capturing variations in economic and market conditions. The EPU reflects shifts in economic and policy uncertainty (Armelius et al., 2017), while the Yield Curve, calculated here as the spread between the 3-month Treasury bill rate and the 2-year government bond yield, serves as a reliable indicator of macroeconomic trends and potential recessions (Baker et al., 2016). Incorporating these indicators makes it possible to assess whether the climate factors offer additional information beyond what these measures already capture.

Table 1: Pairwise Correlation Matrix of Climate and Market Factors

	Swedish Climate Policies	Energy Transition Policies	International Climate Agreements	Global Warming	Mkt-Rf	SMB	HML	MOM	RMW	CMA	Yield Curve	EPU
Swedish Climate Policies	1.00	0.04	0.19	0.07	0.05	-0.02	0.02	0.00	0.00	0.00	-0.15	0.08
Energy Transition Policies		1.00	0.07	0.00	0.03	-0.02	0.01	0.00	-0.01	0.00	-0.04	0.09
International Climate Agreements			1.00	0.23	0.06	-0.01	0.00	0.00	-0.02	0.01	-0.20	0.14
Global Warming				1.00	0.05	-0.01	-0.01	0.00	-0.03	0.00	-0.17	0.15
Mkt-Rf					1.00	-0.25	0.04	-0.05	-0.05	-0.05	-0.05	0.11
SMB						1.00	-0.10	0.02	-0.15	0.04	0.02	-0.04
HML							1.00	-0.17	0.06	0.01	0.01	-0.02
MOM								1.00	-0.22	0.06	0.01	0.01
RMW									1.00	-0.14	-0.02	-0.01
CMA										1.00	0.03	-0.01
Yield Curve											1.00	-0.38
EPU												1.00

Notes: Entries report the pairwise Pearson correlations between the textual climate risk factors and market variables over January 1st, 2000 – December 31st, 2023. The set of variables includes the Fama-French factors (HML, SMB, MOM, RMW, and CMA), the market factor (Mkt-Rf), the Yield Curve (calculated as the spread between the 3-month Treasury bill rate and the 2-year government bond yield), and the Economic Policy Uncertainty Index (EPU) (Armelius et al., 2017). All time series are daily.

The results of the correlation matrix reveal that the pairwise correlations among the climate textual factors Global Warming, Energy Transition Policies, International Climate Agreements, and Swedish Climate Policies, are relatively low, with none exceeding 0.23. The low pairwise correlations among the climate textual factors are a desirable outcome because they validate the effectiveness of the textual analysis methodology. This indicates that each factor captures a distinct dimension of topics around climate risk, confirming that the approach has successfully separated the multifaceted elements of climate change. The low correlations between the climate textual factors and the Fama-French factors suggest that the climate factors provide novel information not already captured by traditional financial risk factors. Moreover, the minimal correlations between the climate factors and macroeconomic variables, represented by the Yield Curve and the EPU, indicate that the climate factors isolate unique risks not reflected in broader economic indicators.

Furthermore, the supplementary Appendix (Tables B4, B5, and B6) shows Variance Inflation Factor (VIF) values well below the threshold of 5, indicating minimal multicollinearity between factors. Weekly variations in the Fama-French factors, displayed in Figure B1, further confirm the stability and independence of the market measures used. The weekly time series plots exhibit the characteristic noise and volatility expected in financial data, with occasional spikes likely reflecting the impact of significant market events, such as the global financial crisis, the European debt turmoil, and the COVID-19 pandemic, which can induce abrupt shifts in investor sentiment and market dynamics.

Overall, this analysis confirms that the climate textual factors and Fama-French factors are distinct and independent, providing a basis for incorporating them into asset pricing models. The next step involves integrating the climate factors into the asset pricing framework, where the Fama-French and Carhart models will be employed to evaluate how these newly developed climate risk measures influence excess returns in the Swedish equity market.

6 Empirical Analysis of Climate Risk Factors on Asset Pricing

Having established the factors to capture media coverage of climate-related topics using LDA, and created corresponding Fama-French factors from the Swedish market, this chapter now empirically tests how these identified climate factors integrate into financial markets. It investigates explicitly whether the climate risk factors are actively priced into the Swedish equity market. Through a series of asset pricing tests, including regression analysis, portfolio sorting, and using a long-short strategy for performance evaluation, this analysis aims to determine to what extent the market perceives and values climate risks.

6.1 Asset Pricing Assessments

Building on the foundational understanding of climate risks derived from the textual analysis, I investigate the hypothesis that climate factors are priced in the cross-section of Swedish stocks. Making use of the non-parametric portfolio sorting method, my approach allows for an investigation into the non-linear relationships between expected returns and climate factors.

The regression model used to incorporate the climate factors and estimate their corresponding sensitivities, referred to as climate betas, is expressed as follows:

$$r_{i,t} - r_{f,t} = \alpha_i + \beta_i F_t + \gamma_i' X_t + \epsilon_{i,t}, \tag{4}$$

Where the terms are defined as:

- $r_{i,t}$: The daily return on security i at time t.
- $r_{f,t}$: The risk-free rate of return at time t,
- F_t: The climate textual factors derived from LDA, representing thematic exposures at time t.
- X_t: A vector of control variables corresponding to the specific Fama-French model being applied.[4]
- $\epsilon_{i,t}$: The error term is assumed to be independently and identically distributed.

Each climate factor derived from the LDA is run individually across the different Fama-French frameworks. This approach allows for a thorough examination of how each specific climate-related topic influences asset prices under varying model specifications, thereby capturing potential variations in their pricing dynamics across different dimensions of market behaviour. This approach is consistent with Faccini et al. (2023) and Chang et al. (2013), who employ rolling windows to capture evolving market conditions. Following their methodology, I use a three-month rolling window for daily observations, advancing it by one month at each step, to track short-term fluctuations in how much each topic is discussed in the media and to relate these shifts to corresponding changes in market returns.

[4] The Fama-French models integrated into X_t include the FF3 (Three-Factor Model) with market return, size (SMB), and value (HML) factors; the FF4 (Four-Factor Model) which extends FF3 by adding Carhart's momentum factor (MOM); and the FF5 (Five-Factor Model) which builds on FF3 by including profitability (RMW) and investment (CMA) factors.

The climate factors identified through LDA remain fixed and time-invariant. Once a topic, such as "Global warming", is defined by a set of characteristic terms, that definition remains unchanged throughout the analysis. For example, if "Global warming" is identified by words like "climate", "emissions", and "temperature" at the start of the study, then that same grouping of words consistently defines the "Global warming" topic at all following periods. By holding these thematic definitions constant, any variations in financial outcomes can be directly attributed to changes in how frequently or intensely these established themes are discussed rather than to shifting or reinterpreted topic definitions. Thus, the analysis more accurately captures how investor sentiment and market reactions respond to consistent climate-related risks over time, reflecting the importance of stable thematic definitions in understanding the evolution of market behaviour (Engle et al., 2020; Faccini et al., 2023).

6.2 Interpretation of beta

A positive climate beta indicates that a stock's returns are positively correlated with an increase in climate risk factors. This correlation suggests that the stock might benefit from climate-related developments or is perceived as resilient to changes in climate policies or conditions. Essentially, stocks with a positive beta are seen as well adapted to handle or even capitalize on climate change related news. Conversely, a negative climate beta implies that a stock's returns decrease as climate risk factors intensify. This relationship indicates that the stock is adversely affected by climate risks, possibly due to vulnerabilities to climate policies, regulations, or physical impacts related to climate change. Stocks with a negative beta are viewed as more vulnerable to losses in scenarios of heightened climate risk, reflecting a higher perceived investment risk during times of escalating climate concerns. This distinction is essential for understanding how different stocks are expected to perform in response to changes in climate risk, influencing investment strategies and portfolio management decisions based on expected climate risk stability or vulnerability.

6.3 Portfolio sorting analysis

Stocks are ranked and sorted monthly based on their estimated climate betas, derived from the climate risk factors. The sorted stocks are then placed into quintile (5 portfolios, corresponding to 20-percent increments) and decile (10 portfolios, corresponding to 10-percent increments) groups to capture varying degrees of sensitivity to climate-related risks. This classification offers a detailed analysis of how different degrees of exposure to climate risks influence asset returns. Value-weighted returns are used to assess the portfolios, giving proportionally greater influence to larger firms in the overall return calculation. This weighting approach, which bases each stock's contribution on its market capitalization, offers a more realistic view of how the market responds to climate risks.

To test the hypothesis that stocks with different climate betas exhibit distinct performance characteristics, a long-short spread strategy is implemented. This strategy involves taking a long position in the portfolio of stocks with the highest climate betas (either quintile portfolio 5 or decile portfolio 10) and a short position in the portfolio with the lowest climate betas (either quintile portfolio 1 or decile portfolio 1). The returns are computed as $\text{Returns}_{\text{Highest Portfolio}} - \text{Returns}_{\text{Lowest Portfolio}}$, measuring the performance impact attributed to different levels of exposure to climate risks. This method effectively isolates the impact of climate sensitivity on stock returns by contrasting the performance at the extremes of climate risk exposure, similar to methodologies employed in other asset pricing studies that explore market anomalies (Gu et al., 2020; Bali et al., 2016; Faccini et al., 2023).

Fundamental to this analysis is the calculation and interpretation of alpha, the intercept in the regression model. This measures the abnormal return in the portfolio spread after accounting for the known risk factors defined in the model, such as market, size, value, and specific climate risks. Alpha is calculated to determine whether stocks, categorized by their sensitivity to climate risks, produce returns that exceed what is predicted by these risk factors. By evaluating alpha, the study assesses whether investors receive compensation for climate-related risks, offering insights into the effectiveness of market mechanisms in integrating these risks into asset pricing.

7 Results

This chapter presents the empirical findings on the pricing of climate risks in the Swedish stock market. Firstly, it examines the results from the asset pricing tests using quantile and decile portfolio sorts based on climate beta measures, highlighting how exposure to various climate news factors impacts abnormal returns (alphas). Secondly, a subsample analysis contrasts market behaviour before and after the Paris Agreement, revealing shifts in investor responses. Lastly, the chapter explores portfolio characteristics to provide context for the observed pricing dynamics.

7.1 First Results

Tables 2 and 3 present the estimated alphas (in % per month) and their t-statistics (in parentheses) for long-short portfolios formed based on stock sensitivities to various climate textual factors. These results cover the Fama-French Three-Factor (FF3), Four-Factor (FF4), and Five-Factor (FF5) models. Specifically, Table 2 details the outcomes for quantile portfolios across Panels A, B, and C, while Table 3 outlines the results for decile portfolios in corresponding panels. All regressions are presented in Appendix C, employing Newey-West t-statistics with six lags (Newey and West, 1987). This adjustment corrects the standard errors for heteroskedasticity and autocorrelation up to six periods back, enhancing the reliability of statistical inferences under these conditions.

The results consistently indicate that Energy Transition Policies are significantly priced in the Swedish stock market. Specifically, stocks with higher positive sensitivity to energy transition news, are associated with lower returns, as evidenced by the negative and significant alphas. In the quintile analysis, the alpha for Energy Transition Policies is -0.34% per month (approximately -4.1% annually). Here, alpha represents the abnormal monthly return unexplained by the standard risk factors, indicating that the highest beta portfolio demonstrates lower annual performance) and significant at the 5% level in the Fama-French Three-Factor Model. This pattern persists in the Four-Factor Model, with an alpha of -0.36% per month (approximately -4.3% annually), even more significant at the 1% level, and in the Five-Factor Model, where the alpha is -0.26% per month (approximately -3.1% annually). The decile analysis aligns with these findings, with alphas remaining negative across models, although the significance slightly diminishes in the Five-Factor Model. These results suggest that stocks more positively correlated with energy transition news, indicating higher exposure to energy transition opportunities, tend to underperform in terms of abnormal returns after adjusting for standard risk factors.

For Swedish Climate Policies, the results are mixed. In the quintile analysis, the alpha is negative but not statistically significant in the Three-Factor Model. However, it becomes significant in the Four-Factor Model at -0.24% per month and significant at the 5% level, suggesting that stocks more positively sensitive to Swedish climate policy news may underperform after accounting for yearly momentum. In the Five-Factor Model, the alpha decreases to -0.13%, losing statistical significance. The decile analysis shows a similar trend, with negative alphas, but not significant. These findings imply that while there may be some pricing of risks associated with Swedish climate policies, the effect is less robust compared to energy transition policies.

Table 2: Quantile Portfolio Sorts Analysis: Climate Textual Factors, Jan 1st, 2000 - Dec 31st, 2023.

Swedish Climate Policies	Energy Transition Policies	International Climate Agreements	Global Warming
Panel A: Fama-French Three-Factor Model			
-0.12	-0.34**	0.02	0.09
(-0.976)	(-2.394)	(0.182)	(0.823)
Panel B: Fama-French-Carhart Four-Factor Model			
-0.24**	-0.36***	-0.02	-0.04
(-2.430)	(-3.451)	(-0.129)	(-0.405)
Panel C: Fama-French Five-Factor Model			
-0.13	-0.26**	0.10	0.17
(-1.260)	(-2.128)	(0.612)	(1.415)

*Note: Entries display the alpha of the spread portfolio, estimated from monthly post-ranking returns, over January 1st, 2000 - December 31st, 2023; the unit is % per month. Significance is denoted by * for the 10% level ($|t| > 1.645$), ** for the 5% level ($|t| > 1.96$), and *** for the 1% level ($|t| > 2.576$), where $|t|$ denotes the absolute value of the t-statistic. T-statistics are reported in parentheses.*

The factors related to International Climate Agreements and Global Warming do not exhibit statistically significant alphas in either the quintile or decile analyses. These results suggest that stocks' sensitivities to news about international climate policies and global warming do not significantly impact their abnormal returns in the Swedish market during the sample period. This may be because investors perceive these broader factors as having a less direct or immediate impact on Swedish companies, possibly due to the country's geographical location or effective mitigation strategies, resulting in long-term risks that are not yet fully integrated into current stock prices. This finding aligns with studies like Manela and Moreira (2017), Hong et al. (2019), and Faccini et al. (2023), which report that physical climate risks do not significantly impact asset prices in certain contexts.

The observed negative alphas in portfolios focused on Energy Transition Policies (Topic 12) and Swedish Climate Policies (Topic 3) are closely linked to Sweden's robust legislative framework and its commitment to climate agreements. Following the Paris Agreement, Sweden's Climate Act of January 1, 2018, established a net-zero emissions goal by 2045, introducing more direct and mandatory requirements on firms than broader international agreements. This provides clear, stable guidelines for reducing greenhouse gas emissions, lowering the risk premium investors typically demand by minimizing the likelihood of unforeseen regulatory changes. Companies following these local policies often adopt more sustainable and efficient practices that mitigate environmental impact while enhancing long-term profitability and resilience. These attributes also make them attractive as hedging strategies. Additionally, firms leading in sustainability may gain brand loyalty and access to green financing, further justifying lower expected returns due to reduced risk. Consequently, negative alphas can arise from the short-term costs and risk-premium reductions associated with strict local regulations, which also explains why the factor capturing International Climate Agreements remains statistically insignificant.

The consistent negative alphas can also be interpreted through an intertemporal hedging motive. An increase in the textual factor of Energy Transition Policies reflects increased policy attention toward accelerating

Table 3: Decile Portfolio Sorts Analysis: Climate Textual Factors, Jan 1st, 2000 - Dec 31st, 2023.

Swedish Climate Policies	Energy Transition Policies	International Climate Agreements	Global Warming
Panel A: Fama-French Three-Factor Model			
-0.10	-0.26*	0.14	0.03
(-0.677)	(-1.741)	(0.851)	(0.227)
Panel B: Fama-French-Carhart Four-Factor Model			
-0.16	-0.26**	0.16	-0.06
(-1.198)	(-1.965)	(0.922)	(-0.398)
Panel C: Fama-French Five-Factor Model			
-0.18	-0.28	0.28	-0.11
(-1.269)	(-1.581)	(1.579)	(-0.599)

*Note: Entries display the alpha of the spread portfolio, estimated from monthly post-ranking returns, over January 1st, 2000 - December 31st, 2023; the unit is % per month. Significance is denoted by * for 10% level (|t| > 1.645), ** for 5% level (|t| > 1.96), and *** for 1% level (|t| > 2.576), where |t| denotes the absolute value of the t-statistic. T-statistics are reported in parentheses.*

the transition to a low-carbon economy. For companies lagging in sustainability or heavily reliant on fossil fuels, this surge signals "bad news" in potential regulatory costs, stricter compliance requirements, or shifting consumer preferences. Conversely, for companies already aligned with sustainable practices, the same development can be "good news", representing opportunities for growth and competitive advantage. In practice, investors may respond to these climate-related shocks by selling or shorting stocks with negative climate betas and buying those with positive climate betas. This behaviour raises the prices of sustainable stocks, thereby reducing their expected returns and contributing to the observed negative alphas.

As discussed in this thesis, the literature supports the notion that climate policies influence asset pricing through risk mitigation and shifting investor preferences. Bolton and Kacperczyk (2021) illustrates how regulatory frameworks can lead to brown premiums, where investors demand higher returns for holding carbon-intensive assets due to elevated risks. Conversely, Alessi et al. (2021) examines the greenium, where sustainable assets command a premium owing to lower perceived risks and increased demand from ethically driven investors. In the Swedish context, comprehensive policy measures demonstrate how effective climate policies shape investment outcomes, thereby explaining the trends observed in asset pricing within Swedish financial markets. Despite these explanations, it remains uncertain how long these negative alphas have persisted and whether significant policy milestones like the Paris Agreement and the Swedish Climate Act have influenced them.

7.2 An Explanation: The Role of Hedging and the Paris Agreement

To validate this hedging explanation for the existence of a negative risk premium associated with the Energy Transition Policies factor, I conduct a subsample analysis by splitting the sample period from the Paris Agreement of December 12, 2015. The Paris Agreement marked a significant moment in global climate policy, with countries committing to substantial reductions in greenhouse gas emissions. This global commitment likely intensified investors' perceptions of transition risks and their impact on asset valuations. Studies such as Bua et al. (2022) documented heightened importance of climate risks since the time of the Paris Agreement, in conjunction with findings from Bolton and Kacperczyk (2021, 2023), Goldsmith-Pinkham et al. (2023), Krueger et al. (2020), and Painter (2020) which collectively emphasize the evolving dynamics of climate-related financial risks in investment decision-making post-2015.

In the post-Paris Agreement period, the quantile portfolio analysis in Table 4 demonstrates a more pronounced and statistically significant negative alpha for portfolios sorted on the Energy Transition Policies factor, consistent across various models. For instance, the Fama-French-Carhart Four-Factor Model in Panel A shows an alpha of -0.49% per month (approximately -5.9% annually), significant at the 1% level, compared to a Pre-Paris alpha of -0.36% per month (approximately -4.3% annually), which had lesser magnitude and significance. Similarly, Panel B's application of the Fama-French Three-Factor Model reveals a Post-Paris alpha of -0.20% per month (approximately -2.4% annually), achieving significance at the 1% level. This contrasts with the Pre-Paris alpha of -0.51% per month, which was significant only at the 10% level, highlighting the increased statistical differentiation post-agreement. Furthermore, a change is observed in the impact of Swedish Climate Policies on portfolio performance. Before the Paris Agreement, portfolios under this factor showed a negative alpha of -0.33% per month (approximately -4.0% annually), significant at the 5% level. After the agreement, the alpha decreased to -0.10% per month and failed to reach statistical significance. In contrast, the decile portfolio sorts in Table 5 exhibit a consistent lack of significance across all models and topics, a phenomenon likely attributable to the increased diversification inherent in splitting the dataset into finer segments (10% each). This segmentation dilutes the observable impacts of specific policy changes, such as those introduced by the Paris Agreement, by mixing varying levels of exposure within each group. Consequently, effects that might be prominent in broader quantile sorts (20% each) are less detectable in decile sorts due to their greater granularity.

These findings suggest that the Paris Agreement served as a catalyst, increasing investor awareness of transition risks and their potential impact on asset valuations. Before the agreement, negative alphas tied to Energy Transition Policies were smaller and less consistent, indicating that investors might not have viewed global climate commitments as urgent or financially impactful. However, the marked increase in negative alpha significance in the post-Paris period indicates that, once the global policy landscape became clearer, investors adjusted their portfolios to hedge against these emerging risks. This shift is highlighted by stronger negative alphas, reflecting a more systematic approach to pricing transition exposures as markets recognized both the growing momentum behind climate actions and the potential economic consequences for affected firms.

However, it remains unclear whether these adjustments in investment strategies are driven by a brown premium, characterized by higher returns demanded by investors for firms with lower climate betas (Bolton and Kacperczyk, 2021), or by a greenium, where lower returns are accepted for green investments with higher betas (Alessi et al., 2021), or a combination of both.

Table 4: Quantile Portfolio Sorts Analysis: Pre- and Post-Paris Agreement

Swedish Climate Policies		Energy Transition Policies		International Climate Agreements		Global Warming	
Pre-Paris	Post-Paris	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris
Panel A: Fama-French Three-Factor Model							
-0.23	0.001	-0.51*	-0.20***	0.09	0.02	0.25	-0.02
(-1.319)	(0.005)	(-1.959)	(-2.611)	(0.583)	(0.103)	(1.522)	(-0.173)
Panel B: Fama-French-Carhart Four-Factor Model							
-0.33**	-0.10	-0.36**	-0.49***	0.13	-0.004	0.06	-0.11
(-2.240)	(-1.004)	(-2.177)	(-3.261)	(0.691)	(-0.024)	(0.395)	(-0.718)
Panel C: Fama-French Five-Factor Model							
-0.09	-0.02	-0.28	-0.11	0.09	0.03	0.31	0.03
(-0.593)	(-0.146)	(-1.605)	(-1.022)	(0.428)	(0.180)	(1.921)*	(0.136)

Table 5: Decile Portfolio Sorts Analysis: Pre- and Post-Paris Agreement

Swedish Climate Policies		Energy Transition Policies		International Climate Agreements		Global Warming	
Pre-Paris	Post-Paris	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris	Pre-Paris	Post-Paris
Panel A: Fama-French Three-Factor Model							
-0.04	-0.11	-0.35	-0.07	0.10	0.27	-0.08	0.20
(-0.161)	(-0.624)	(-1.216)	(-0.535)	(0.376)	(1.140	(-0.307)	(1.215)
Panel B: Fama-French-Carhart Four-Factor Model							
-0.10	-0.04	-0.31	-0.10	0.28	0.19	-0.04	0.001
(-0.443)	(-0.206)	(-1.269	(-0.722)	(1.026)	(0.789)	(-0.181)	(0.047)
Panel C: Fama-French Five-Factor Model							
-0.25	0.09	-0.41	-0.03	0.39	0.15	-0.13	0.08
(-0.933)	(0.410)	(-1.437)	(-0.190)	(1.594)	(0.658)	(-0.445)	0.313

*Note: Entries display the alpha of the spread portfolio, calculated from monthly post-ranking returns, spanning from January 1st, 2000 to December 31st, 2023, presented in % per month. The dataset is divided into periods before and after the adoption of the Paris Agreement on December 12, 2015. Significance levels are marked as * for the 10% level (|t| > 1.645), ** for the 5% level (|t| > 1.96), and *** for the 1% level (|t| > 2.576), with |t| representing the absolute value of the t-statistic. T-statistics are enclosed in parentheses.*

7.3 Portfolio Characteristics

To confirm the drivers, I analyze the characteristics of quantile portfolios sorted by climate beta values to understand shifts in investor behaviour and asset valuations before and after the Paris Agreement. The focus is exclusively on quantile portfolios that showed significance when using the Fama-French Three-Factor (FF3) and Four-Factor (FF4) models to assess the impact of climate policy awareness on financial metrics. Portfolios are arranged in ascending order of climate beta, with Portfolio 1 (Low) comprising stocks that have the most negative climate betas, thus facing higher transition risks. At the same time, Portfolio 5 (High) contains those with the most positive climate betas. Key characteristics assessed include average monthly returns, climate betas related to Energy Transition Policies, total ESG scores, the Environment Pillar Score (E Score), direct and indirect CO_2 equivalents emissions, market capitalization (log) and Return on Assets (ROA).[5]

Pre-Paris Agreement Period

Under the Fama-French Three-Factor Model (Panel A1 of Table 6), Portfolio 1 shows a positive and statistically significant average monthly return of 0.54% (approximately 6.7% annually), whereas Portfolio 5's average return of 0.10% is statistically insignificant. The average climate beta increases from -0.69 in Portfolio 1 to 0.65 in Portfolio 5. Environmental scores improve with higher climate betas, suggesting that firms with more negative climate betas tend to have lower environmental performance. CO_2 emissions data also highlight this pattern. During the Pre-Paris Agreement period, firms in Portfolio 1 register higher direct CO_2 equivalent emissions, averaging about 494.20 thousand metric tonnes, compared to approximately 306.76 thousand metric tonnes in Portfolio 4 and 350.05 thousand metric tonnes in Portfolio 5. Indirect emissions show less variation, remaining relatively stable across the portfolios. This indicates that firms with more negative climate betas, which carry greater transition risks, tend to exhibit higher direct emissions, consistent with their lower environmental performance.

Firms in Portfolios 2–4 generally have larger market capitalizations, as indicated by log(Size) values between 7.35 and 7.47, compared to the smaller firms in Portfolios 1 and 5, where log(Size) are around 6.89 and 6.96. Return on Assets (ROA) is negative for the extreme portfolios (1 and 5), at -4.64% and -2.45%, respectively, suggesting lower profitability at both ends of the climate beta spectrum. In contrast, the middle portfolios report positive ROA values. Under the Fama-French-Carhart model (Panel B1), these results remain broadly consistent. Portfolio 1 continues to show a positive and statistically significant average monthly return of 0.44% per month (approximately 5.3% annually), whereas Portfolio 5 remains insignificant with an average monthly return of 0.08%. Climate betas average from -0.70 in Portfolio 1 to 0.656 in Portfolio 5, mirroring the pattern observed under the Three-Factor Model.

[5]Data retrieved from Refinitiv Eikon.

Table 6: Energy Transition Policies Textual Factor: Portfolio Characteristics

	Portfolio				
	1 (L)	2	3	4	5 (H)
Panel A1: Pre-Paris Agreement (Fama-French Three-Factor Model)					
Return	0.54**	0.31	0.34**	0.08	0.10
	(2.37)	(1.55)	(2.10)	(0.52)	(0.05)
Climate β	-0.69	-0.19	-0.016	0.15	0.65
ESG Score	62.13	62.60	62.82	61.88	61.59
E Score	63.59	65.16	65.98	65.11	64.57
CO2 Equivalents Emission Direct	494.20	419.75	338.52	306.76	350.05
CO2 Equivalents Emission Indirect	210.49	225.12	205.91	202.14	216.33
log(Size)	6.89	7.35	7.47	7.37	6.96
ROA	-0.046	0.04	0.043	0.043	-0.025
N	170	169	169	168	169
Panel A2: Post-Paris Agreement (Fama-French Three-Factor Model)					
Return	0.43***	0.21*	0.20	0.08	0.23*
	(3.17)	(1.90)	(1.55)	(0.64)	(1.72)
Climate β	-0.74	-0.21	-0.01	0.20	0.76
ESG Score	54.68	59.08	60.18	58.87	56.35
E Score	48.93	55.12	57.62	56.43	51.85
CO2 Equivalents Emission Direct	212.91	139.41	161.06	162.32	208.71
CO2 Equivalents Emission Indirect	66.83	71.09	80.46	73.34	65.62
log(Size)	6.86	7.42	7.55	7.41	6.92
ROA	-0.085	0.012	0.015	0.008	-0.09
N	467	475	475	475	471
Panel B1: Pre-Paris Agreement (Fama-French-Carhart Four-Factor Model)					
Return	0.44**	0.30	0.276*	0.13	0.08
	(2.22)	(1.50)	(1.73)	(0.74)	(0.40)
Climate β	-0.70	-0.193	-0.018	0.153	0.656
ESG Score	62.08	62.59	62.19	62.47	61.91
E Score	63.58	65.21	65.41	65.70	64.62
CO2 Equivalents Emission Direct	514.06	409.51	328.37	307.14	370.38
CO2 Equivalents Emission Indirect	220.35	219.96	204.48	203.28	219.37
log(Size)	6.91	7.35	7.46	7.37	6.96
ROA	-0.046	0.04	0.045	0.042	-0.027
N	170	169	169	169	169

Continued on next page

Table 6 – Continued from previous page

	Portfolio				
	1 (L)	2	3	4	5 (H)
Panel B2: Post-Paris Agreement (Fama-French-Carhart Four-Factor Model)					
Return	0.61***	0.21**	0.165	0.14	0.12
	(3.23)	(2.16)	(1.29)	(1.13)	(1.09)
Climate β	-0.744	-0.214	0.00	0.20	0.766
ESG Score	54.46	59.25	60.08	58.83	56.51
E Score	48.75	55.20	57.59	56.34	52.08
CO2 Equivalents Emission Direct	181.23	150.70	148.22	181.38	187.11
CO2 Equivalents Emission Indirect	64.48	73.53	76.36	76.91	64.80
log(Size)	6.86	7.41	7.56	7.40	6.94
ROA	-0.085	0.009	0.018	0.007	-0.09
N	467	475	475	475	471

*Note: Entries report average values at a portfolio level for all variables including average monthly returns, climate betas, ESG scores, Environment Pillar Score, CO2 emissions in thousand metric tonnes, the firm size (log of average market capitalization), return on assets (ROA) and the average number (N) of firms for each portfolio. These averages span from January 1st, 2000, to December 31st, 2023, and are presented in % per month for returns. The dataset is divided into periods before and after the adoption of the Paris Agreement on December 12, 2015. Significance levels for returns are marked as * for the 10% level (|t| > 1.645), ** for the 5% level (|t| > 1.96), and *** for the 1% level (|t| > 2.576), with |t| representing the absolute value of the t-statistic. T-statistics are enclosed in parentheses.*

Post-Paris Agreement Period

After the Paris Agreement, the pattern of returns undergoes slight shifts. In the Fama-French Three-Factor Model (Panel A2), Portfolio 1 still shows a positive and significant average monthly return of 0.43%, while Portfolio 5's average return now becomes marginally significant at 0.23%; however, this significance is only at the 10% level, indicating a lack of statistical robustness. Climate betas continue to span from -0.74 (Portfolio 1) to 0.76 (Portfolio 5). Environmental scores decline in both Portfolios 1 and 5 following the Paris Agreement. For example, Portfolio 1's ESG score decreases from 62.13 Pre-Paris to 54.68 Post-Paris, and its Environment Pillar Score falls from 63.59 to 48.93. CO_2 emissions also diminish across all portfolios in the Post-Paris period. For instance, Portfolio 1's direct CO_2 equivalents emissions drop from approximately 494.20 thousand metric tonnes Pre-Paris to 212.91 thousand metric tonnes Post-Paris, while indirect emissions decline from about 210.49 to 66.83 thousand metric tonnes.

Firms in the middle portfolios remain larger, with log(Size) values around 7.41-7.55, while Portfolio 1 and 5 firms are smaller at 6.86 and 6.92, respectively. Profitability remains low for these extreme climate beta portfolios, with ROA still negative in Portfolios 1 and 5 (-8.54% and -9.11%), signalling persistent challenges for these firms. Results under the Fama-French-Carhart model (Panel B2) are qualitatively similar. Portfolio 1's monthly return remains positive and significant at 0.61%, and Portfolio 5's return stays statistically insignificant at 0.12%. Climate betas again span from about -0.744 to 0.766, consistent with the Three-Factor model.

The observed results provide support for the brown premium hypothesis, which posits that investors demand higher returns for holding brown firms, those with lower climate betas and greater exposure to energy transition risks (Bolton and Kacperczyk, 2021). Specifically, the significant positive average return for Portfolio 1 (Low Climate Beta), both Pre- and Post-Paris Agreement, indicate that investors are compensating for the heightened transition risks associated with these firms by requiring higher expected returns. This is further confirmed by the consistent significance of these alphas across the Fama-French Three-Factor and Four-Factor Models. Conversely, the lack of statistically significant alphas for Portfolio 5 (High Climate Beta) suggests that there is no empirical evidence for a greenium within the observed dataset (Alessi et al., 2021).

A noteworthy point is that Portfolios 1 and 5 share several characteristics, including lower ESG scores and higher CO_2 emissions, an observation that may initially appear counterintuitive. This finding, however, aligns with the insights of Faccini et al. (2023), Engle et al. (2020), and Ardia et al. (2023), who show that hedging strategies can incorporate both "brown" and "green" firms. The presence of high-emission firms in Portfolio 5, despite their higher climate betas, reflects the complex interplay between ESG metrics and emissions. Firms in Portfolio 5 may invest in green innovations to manage their carbon footprint yet still demand higher returns because of their exposure to carbon-intensive processes. Theoretical perspectives from Pastor et al. (2021) and Baker et al. (2022) further suggest that some brown firms may act as hedges if their emissions correlate with positive output shocks.

The shifts in the emissions data displayed in the tables before and after the Paris Agreement might prompt questions regarding the drivers behind these changes. Refined accounting methodologies, evolved reporting standards, and structural transformations within the sampled firms can partly explain the noted declines in reported emissions. A significant reduction in emissions, approximately 17.79% from the first quarter of 2016 to the fourth quarter of 2023, highlights a marked decrease (Statistics Sweden, 2023). Additionally, a shift from higher-emitting sectors such as 'Industrials' to lower-emission sectors like 'Healthcare' has likely contributed to the downward trend. As shown in Figure C1 and Figure C2, 'Healthcare' is present in both high- and low-beta portfolios, reflecting the variety of sub-industries within the sector, from biotech companies with low energy intensity to pharmaceutical production with higher emissions. Furthermore, a notable increase in IPO activity in the Nordic region, particularly in Sweden, post-COVID-19, led to significant shifts in market compositions, influencing sectoral market shares and increasing the number of active companies in the market (Wass and Ahmad, 2021). This can also be seen in the increase in the number of firms (N), driven by more firms entering the market as well as enhanced disclosure of environmental impact, evidenced by the reporting of ESG and E scores. However, this alone likely does not account for the overall decline observed.

The enhancement of the Greenhouse Gas Protocol's Scope 2 Guidance in 2015, along with subsequent updates to Scope 3 reporting, might have reallocated certain emissions to different categories, affecting the apparent total emissions (World Resources Institute, 2015; IPCC, 2014). Additionally, improvements in measurement methods, guided by the IPCC's Fifth Assessment Report in 2014, may have resulted in adjustments to CO2 equivalent calculations (IPCC, 2014). Further complicating the analysis, the enhancements in greenhouse gas accounting practices over recent years, including improved accuracy in emission factor databases and better alignment of national inventories with international reporting standards (IPCC, 2019), have potentially contributed to more accurate and possibly lower emission reports. These factors together suggest that while actual reductions in emissions are a positive indicator, changes in reporting methodologies and accounting standards are also influential in the apparent reductions seen Post-Paris Agreement.

While these considerations are important for understanding broader environmental policy and corporate sustainability strategies, they lie beyond the analytical scope of this thesis. Investigating the causes of observed differences in emissions measurement or the inclusion of different greenhouse gases would require a separate, detailed methodological analysis.

8 Discussion

This section provides an overview of the main findings from the study, which involves measuring and evaluating the impact of news-based climate risks on asset pricing models. Following the summary, the discussion examines the methodologies employed, particularly the LDA and asset pricing models, highlighting their validity and limitations. The section concludes with a discussion of potential avenues for future research.

In this study, I explored the integration of different climate risks into the Swedish equity market by constructing textual climate risk factors and assessing their impact on asset pricing through the application of the Fama-French models. The study aimed to capture both transition and physical climate risks through text-based analysis, providing a nuanced understanding of whether these risks are priced in stock returns in an environmentally progressive market. By using advanced NLP techniques to examine a large corpus of articles from prominent Swedish publishers, I produced textual climate risk indexes. Utilizing techniques such as TF–IDF and LDA, I developed specialized corpora and identified latent topics related to climate risks. The TF–IDF approach allowed me to construct transition and physical risk vocabularies derived from authoritative climate change texts, ensuring a rigorous selection of relevant terms to guide the identification of news article corpora related to these categorical risks. LDA enabled me to uncover hidden thematic structures within the articles, leading to the identification of four key topics: Swedish Climate Policies, Energy Transition Policies, International Climate Agreements, and Global Warming. To evaluate whether the identified climate risks were priced into the Swedish stock market, I integrated the constructed textual climate risk factors into the asset pricing framework using the Fama-French Three-Factor, Four-Factor, and Five-Factor models. I estimated alphas (abnormal returns) of portfolios formed based on stocks' sensitivities to the climate risk factors, here called climate betas. By sorting stocks into quintile and decile portfolios according to their climate betas, with the lower portfolios representing lower climate betas and the higher portfolios representing higher climate betas, I effectively grouped companies by their exposure to specific climate risks.

The findings reveal that the negative abnormal returns (alphas) associated with the Energy Transition Policies factor become significantly more pronounced after the Paris Agreement, indicating that stocks with higher climate betas underperform once standard risk factors are accounted for. This shift suggests heightened investor awareness and integration of strategic pricing of climate-related risks in financial markets, aligning with global climate commitments. From these results, several learnings can be identified about how climate-related risks and policies are integrated into the Swedish equity market.

Firstly, the pronounced and statistically significant negative alphas, abnormal return, associated with the Energy Transition Policies factor, especially after the Paris Agreement, highlight that investors increasingly price in energy transition risks. The heightened significance of negative alphas in the Post-Paris period suggests that as global climate commitments intensify, market participants become more sensitive to transition-related uncertainties in affected firms, demanding higher returns to compensate for perceived regulatory and operational challenges. This dynamic, characterized by the presence of a brown premium, where low climate beta (brown) portfolios consistently exhibit positive and significant alphas both before and after the Paris Agreement

(Bolton and Kacperczyk, 2021), aligns with the findings of Bua et al. (2022) and Faccini et al. (2023), which demonstrate that climate policy news significantly impacts stock returns. This implies that investors have long recognized the elevated risks facing these firms but that these risks became even more salient following a major international policy milestone, resulting in higher risk premiums. Notably, these portfolios with lower betas are characterized by lower average ESG and environmental scores and higher direct CO2 emissions, factors that likely contribute to the perceived higher risk and thus demand greater returns. Secondly, while high climate beta (green) portfolios often show lower returns, this pattern is not pronounced enough to confirm a greenium in the Swedish context (Alessi et al., 2021). In other words, aligning with sustainability objectives does not guarantee consistently lower required returns, at least not within the timeframe and conditions examined. This finding suggests that while green attributes are valued, they do not automatically translate into reduced cost of capital in environments like Sweden, where regulatory stability and a longstanding commitment to sustainability might already be priced into the market.

Additionally, research by Faccini et al. (2023) on U.S. climate policy factors shows a different pattern. Their analysis indicates positive and statistically significant abnormal return for portfolios with higher climate betas, impacted by U.S. climate policy changes, suggesting that these firms achieve higher returns than predicted by traditional risk models. This suggests that U.S. investors demand a risk premium for stocks influenced by climate policies, likely due to greater regulatory uncertainty and anticipated compliance costs. In contrast, the Swedish Climate Policies factor did not yield significant alphas post-Paris Agreement and showed negative alphas prior to it. This discrepancy may stem from Sweden's relatively stable and predictable climate policy environment (Basseches et al., 2022). Because Swedish investors likely incorporated expectations of these policies well in advance, the introduction of new policy signals following the Paris Agreement offered little additional uncertainty to justify a risk premium. Furthermore, Sweden's longstanding commitment to sustainability could mean that both firms and investors have long been operating under the assumption that climate considerations are integral to strategic and financial decision-making. As a result, unlike in the U.S. context, simply signalling climate policy shifts in Sweden does not translate into reliably higher or lower abnormal returns.

These observations highlight the nuanced integration of climate-related risks into asset pricing. As global climate commitments intensify, the Swedish market demonstrates how ESG considerations and predictable policy environments influence financial valuations, revealing a sophisticated interplay between policy developments, environmental performance, and investment strategies.

8.1 Evaluating the Validity and limitations of LDA method

Measurement Validity

This study employs LDA to construct indicators of climate-related risks based on textual analysis of Swedish news articles. While LDA is a powerful tool for uncovering latent topics within large text corpora, its application introduces several validity concerns. The flexibility of human language necessitates numerous subjective decisions in the measurement design, such as the selection of keywords, the determination of the number of topics, and the tuning of hyperparameters. Even minor adjustments in these parameters can lead to significant variations in the resulting topics and their interpretations (Blei et al., 2003). For instance, altering the number of topics in an

LDA model can drastically change the thematic structure identified, potentially affecting the study's conclusions (Chang et al., 2009).

To mitigate these concerns and enhance the robustness of the measurements, this research employs a grid search approach for hyperparameter tuning. Grid search systematically explores a predefined set of hyperparameters, ensuring that the selection process is based on objective criteria rather than arbitrary choices. This method reduces the researcher's degree of freedom and enhances the reproducibility of the model configurations. Additionally, sensitivity analyses were conducted by varying the number of topics and adjusting keyword sets to evaluate the stability of the results. These analyses involved examining how changes in parameter values affected both the coherence and perplexity scores of the overall model. Furthermore, the analyses assessed how different parameter configurations influenced the thematic structure of topics, ensuring that the selected parameters yielded the most specific and interpretable results. The findings demonstrated that the core conclusions remained consistent across various model specifications, thereby addressing concerns related to parameter sensitivity.

Keyword Selection and Classification Errors

The initial filtering of articles relies on a the defined set of climate-related keywords from the TF-IDF method. While this approach aims to capture relevant content, it is prone to both false negatives and false positives. False negatives may occur if relevant articles discuss climate risks without using the selected keywords. In contrast, false positives may arise if articles mention the keywords without substantive discussion of climate-related issues. Language is inherently dynamic, and the terminology used to discuss climate-related issues can shift over time. This poses a challenge for maintaining the temporal relevance of the keywords used in the analysis. For instance, certain terms may become outdated or be replaced by more contemporary phrases, potentially leading to a mismatch between the keywords and the evolving climate discourse. For example, the Swedish term "*växthuseffekten*" (greenhouse effect) was more prevalent in earlier years, whereas "*global uppvärmning*" (global warming) and "*klimatförändringar*" (climate change) have gained prominence in recent times.

To account for these variations and minimize classification errors, the keyword list was refined by including synonyms and related terms identified through historical analysis of climate discourse in Swedish media. Additionally, preprocessing techniques such as stemming and lemmatization were employed to ensure that different morphological forms of the keywords were properly captured. Despite these efforts, some degree of misclassification remains inevitable. However, the consistent patterns observed across multiple robustness checks, which showed that topics found were primarily around climate topics, suggest that these errors do not substantially undermine the study's internal validity.

Potential for Measurement Error

Measurement error is a potential limitation stemming from the imperfect alignment between the selected keywords and the actual climate risk content of the articles. Articles may discuss climate risks using context-specific language or nuanced expressions that are not fully captured by the keyword list. Conversely, articles may include keywords in contexts unrelated to climate risks, introducing noise into the indicators. To reduce measurement error, the study employed rigorous preprocessing steps, including the removal of stop words, punctuation, and irrelevant content that could lead to false positives. Furthermore, the coherence of the topics generated by the LDA model was evaluated using coherence scores to ensure that the identified topics were semantically meaningful and closely related to climate risks. Topics with low coherence were excluded from the analysis, thereby enhancing the accuracy of the climate risk indicators.

Despite these efforts, LDA might still create overlapping topics or fragment closely related content into different groups. For instance, in this study, Topic 11 (focused on wind power and municipal infrastructure) and Topic 12 (broadly covering green and renewable energy transition) could have been merged into a single topic by using Principal Component Analysis (PCA) to more comprehensively capture the range of energy policies and their local implementations and effectively consolidate these overlapping topics. PCA could help identify the principal components that capture the most variance across topics, offering a clearer and potentially more impactful representation of climate-related discourse. This approach, though potentially useful for grouping related topics, was not applied in this analysis to remain consistent with the methodology of Faccini et al. (2023), which guided the LDA stage of this study.

8.2 Evaluating the Validity and limitations of Asset pricing method

Methodological Foundation and Innovations

The use of Fama-French models in this study is based on their reputation as workhorse frameworks in empirical asset pricing. By applying the Three-Factor, Four-Factor, and Five-Factor models, as well as testing results across different portfolio sorts (e.g., quintile and decile), this approach ensures a certain level of methodological rigor and comparability to earlier studies. The use of multiple Fama-French models also helps ensure that the results are reliable and that the observed effects are not driven by a single model specification. A key strength of this approach is the integration of the climate factors into the traditional asset pricing models. This methodological innovation extends the models to incorporate intangible yet relevant factors related to climate risks, offering a more comprehensive view of how stocks respond to climate-related information in the context of the global shift toward environmentally conscious investment strategies.

Limitations of Traditional Risk Factor Models

However, several limitations must be acknowledged when applying these methods within the present study. While the incorporation of climate betas adds valuable dimensions to the asset pricing models, these models were originally designed to explain return patterns driven by conventional risk factors such as market risk, size, value, profitability, and investment characteristics. As a result, the Fama-French models do not explicitly account for more nuanced or evolving sources of return variation that may arise from intangible, time-sensitive information signals or complex investor behaviours not captured by these standard dimensions. Additionally, although sorting stocks into portfolios based on constructed climate betas contributes to robustness checks, it does not fully address the potential for structural changes in the market environment over time that could make certain factor specifications less relevant. Market regimes and structures can shift, and newly salient risk dimensions, whether financial, macroeconomic, or other types, may develop. The static factor loadings and linear assumptions in these models may fall short of capturing how new information influences prices, particularly if the effects are nonlinear or occur within short windows following significant policy announcements or market shocks.

To address the dynamic nature of market conditions, this study employs a rolling window regression method, recalculating climate betas monthly using the past three months of daily data. This approach ensures the model remains responsive to recent market dynamics and information flows, capturing the immediate effects of climate-related news and shifts in investor sentiment. By frequently updating beta estimates, this method helps track how short-term fluctuations in climate risk perceptions influence stock prices. While this technique allows for continuous adaptation to new information, it may also introduce variability, as the brief observation period might capture temporary effects that do not represent longer-term trends. Nonetheless, the rolling window regression is a potent tool for analyzing the impact of climate-related information on asset prices in a fast-changing environmental and regulatory landscape, providing deep insights into the swift integration of such information into market valuations. However, while standard asset pricing models and rolling window regressions identify correlations or associations, they don't necessarily prove cause and effect. More robust and stronger econometric techniques, such as difference-in-differences, can better address endogeneity and isolate causal impacts. Yet, while these methods provide a refined approach to analyzing causality, the long-term nature of climate change introduces significant analytical challenges. As a result, even advanced methods require careful adaptation to accurately reflect the dynamics of climate change and its implications on financial markets within the constraints of available data.

Furthermore, the OLS regressions estimating alphas for the Energy Transition Policies factor before and after the Paris Agreement reveal modest R^2 values in both the Fama-French Three-Factor (FF3) and Four-Factor (FF4) models. Specifically, FF3 shows R^2 values of 0.025 (Pre-Paris) and 0.013 (Post-Paris), while FF4 presents R^2 values of 0.076 and 0.036 for the respective periods (see Appendix C). Although these R^2 values are low, they align with findings from other studies employing similar methodologies to predict equity returns (Gu et al., 2020). Capturing return variations in financial markets is challenging due to market noise and numerous hidden influences. Consequently, even models with limited explanatory power can provide valuable insights by highlighting specific risks not captured by traditional factors.

Broad Analysis Versus Specific Narrative Insights

The methodology used in this study focuses on broad market patterns, prioritizing methodological objectivity over the granularity of specific narratives. While this approach effectively captures general trends related to climate risk across the market, it limits the depth of analysis into the particular articles or events that trigger these trends. For instance, Faccini et al. (2023) goes deeper into the sentiment dynamics of climate policy by subjectively categorizing news articles as positive, neutral, or negative risks, creating a nuanced time series that tracks the fluctuating sentiment of climate risk over time. Their method allows for a detailed understanding of how shifts in sentiment about U.S. climate policy impact asset prices. In contrast, this study aggregates climate risk factors from a wide range of news articles without differentiating the sentiment or immediate context of individual articles. This broad-scope approach was chosen to minimize subjective bias and ensure consistency across the data set, providing a macro-level insight into how climate risks, as a whole, influence market behaviour. However, this means it does not capture the specific instances or narratives that might explain sudden changes in market behaviour or asset pricing. Therefore, while the findings show the overall impact of climate factors, they lack detailed insights into how particular narratives drive these changes.

8.3 Future Research

This thesis's findings and methodological advancements highlight several promising directions for future research. Firstly, extending the scope of textual climate risk factors and asset pricing tests to other financial instruments, such as corporate bonds, exchange-traded funds (ETFs), and mutual funds, could deepen our understanding of how climate-related risks are integrated across different asset segments of the financial market. Investigating the impact of transition and physical risks on the pricing mechanisms within these asset classes might reveal variances in risk perception and valuation, potentially influencing long-term financial and strategic decision-making. The work by Bachelet et al. (2019) on the green bonds market underlines the significance of issuer characteristics and third-party validation, suggesting similar factors might also affect the pricing dynamics in other sustainable finance instruments.

Secondly, the complex nature of climate-related transition risks demands more sophisticated measurement techniques. Building on the insights from Sveriges Riksbank (2022), there is a stated *"need to combine methods and data sources or supplement the analysis with other methods and tools"* to capture these risks accurately. Advancing this effort, integrating cutting-edge NLP techniques such as transformer-based models like BERT could refine the detection of nuanced linguistic shifts and sentiments (Devlin et al., 2019). These enhancements would enable a more accurate linking of asset price changes to specific climate narratives, offering a more detailed understanding of how sentiment and policy language impact financial markets.

Lastly, adding detailed data from company sustainability initiatives and broader stakeholder perspectives derived from quarterly and annual reports could deepen the analysis of climate risk. By incorporating these data sources alongside advanced NLP and machine learning techniques, future research could also investigate specific industries more deeply than this study, offering a nuanced and thorough examination of the economic impacts of climate risks.

9 Conclusion

This thesis began with the fundamental question: Are climate risks reflected in stock market valuations, particularly within the Swedish market? The importance of this research arises from the growing acknowledgment of climate change as a key factor shaping economic stability and global investment landscapes. Through a detailed investigation that combined innovative NLP techniques with established financial econometric models, this interdisciplinary research has not only addressed a critical gap in understanding the Swedish market's dynamics but also provided valuable insights into the broader discourse on climate risk and asset pricing. The development of climate risk factors using textual analysis marked an important methodological advancement in this study. By extracting and analyzing key topics from a large collection of Swedish news articles spanning two decades, this thesis measured the market's responsiveness to various aspects of climate risk. The integration of these factors into Fama-French asset pricing models further allowed for a detailed evaluation of how these risks are reflected in stock returns, highlighting the distinct effects of physical and transition risks on market valuations.

Key findings indicated a distinct pricing of transition risks associated with shifts towards a low-carbon economy, particularly following the Paris Agreement. Portfolios with negative sensitivity to energy transition policy news exhibited higher returns, demonstrating a "brown premium", which suggests that the market compensates investors for the perceived risks associated with stocks adversely affected by shifts towards a greener economy (Bolton and Kacperczyk, 2021). Contrary to expectations of a "greenium", where lower returns might be accepted for green investments, the study found no significant evidence to support this within the Swedish context, although portfolios with higher climate beta values, indicating positive sensitivity to energy transition news, showed lower returns (Alessi et al., 2021). In contrast to transition risks, physical climate risks like global warming did not show a comparable pricing impact. This may stem from their perception as too broad or long-term to affect immediate asset valuations. These results differ from the broader European market analysis by Bua et al. (2022), which found strong evidence of pricing for these risks, while aligning with (Faccini et al., 2023)'s findings, highlighting variations in market responses shaped by regional regulatory frameworks and levels of market development.

The implications of these findings are broad and significant. For policymakers, the observed influence of energy transition policies on market behaviour can guide the development of targeted regulations aimed at reflecting climate costs in asset pricing. By recognizing that high-emission firms face a "brown premium", governments can strengthen these market signals. Offering tax credits or other incentives to lower-emission companies reduces their financing costs, while imposing stricter standards on carbon-intensive firms makes their capital more expensive. This approach aligns the market's negative view of transition risks with public policy goals, directing investments toward cleaner operations and encouraging lower overall emissions. Large institutional investors, including pension funds, could integrate these insights into their portfolio strategies, aligning financial returns with broader climate objectives. Such measures, informed by the Swedish example, could help other nations and regulatory bodies refine their approaches to managing environmental risks in capital markets without presuming a one-size-fits-all solution.

Nevertheless, this study navigates complex challenges, particularly in the measurement and modelling of climate risk dynamics. The dependency on textual data and the subjectivity in interpreting such datasets introduce a layer of uncertainty in the index construction process. Moreover, traditional asset pricing models, despite their robustness, may not fully account for the entire range of climate risk impacts, particularly those that appear beyond conventional risk parameters.

Future research should expand on this work by using advanced machine-learning techniques to manage and analyze large-scale datasets with greater accuracy. Broadening the analytical scope to cover a variety of financial instruments and markets will deepen the global understanding of how climate risks are perceived and priced. Additionally, adding detailed firm-level report data, sustainability initiatives, and ESG performance will offer richer insights into how these factors influence stock valuations.

In conclusion, this interdisciplinary thesis, which merges financial economics, sustainability, and data science, represents a significant advance in understanding how climate risks intersect with financial markets. It provides insights for strengthening financial systems against environmental risks and serves as a valuable resource for stakeholders throughout the financial ecosystem to make informed, strategic decisions that promote economic growth while contributing to global sustainable development goals. As the world continues to face the challenges of climate change, the innovative research introduced in this thesis will undoubtedly be foundational for future academic and practical applications in sustainable finance.[6] [7]

[6] All codes used in this study, including those for TF-IDF, LDA, Fama-French calculations, and the corresponding regressions for beta and alpha estimations, are available at `https://github.com/johannesthesiscode2024/Thesis-code`. These resources are provided to support further research in this area.

[7] In compliance with the Stockholm School of Economics' guidelines on the use of AI tools in academic work, I wish to disclose that I have used *Grammarly* with the *Academic* setting to assist in proofreading and enhancing the clarity, coherence, and consistency of the text in this thesis.

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Appendix A: Textual Methods

Table A1: Definition of Key NLP and LDA Terminology

Term	**Definition**
Natural Language Processing (NLP)	Artificial intelligence field enabling computers to understand and process human language, used to analyze climate-related texts like news articles and policy documents.
Corpus (*plural: Corpora*)	Large collection of texts for analysis, such as news articles from various Swedish media sources used in this study.
Token	Smallest unit of meaning in text, like a word or phrase, used in the analysis (e.g., "renewable").
Unigram	Single word treated as an individual entity within a text (e.g., "climate").
Bigram	Pair of consecutive words treated as a single token (e.g., "global warming").
Trigram	Sequence of three consecutive words treated as a single token (e.g., "renewable energy investment").
Tokenization	The process of splitting text into individual tokens, such as words or phrases. This step often involves removing punctuation like periods (.), commas (,), semicolons (;), and colons (:) to simplify the data and focus analysis on the textual content.
Lemmatization	Reducing words to their lemma, a word's canonical or dictionary form. This process involves more sophisticated linguistic knowledge to ensure that the transformed word is a valid word in the language (e.g., "better" to "good").

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Term	**Definition**
Stemming	Reducing words to their stem by cutting off the ends of words based on common prefixes and suffixes. This process is less sophisticated than lemmatization and does not ensure that the resulting stem is a valid word (e.g., "running" to "run").
Stop Word	Common words (e.g., "and", "the") removed during preprocessing as they carry minimal semantic value.
TF-IDF	Term Frequency-Inverse Document Frequency, measure evaluating word importance in a document relative to a corpus by considering its frequency and rarity.
LDA	Latent Dirichlet Allocation. Probabilistic model used to discover abstract topics within a corpus, assuming each document is a mixture of topics and each topic is a distribution of words.
Topic Modelling	Technique for identifying topics within a set of documents, with LDA being a common method.
Topic Coherence	Metric assessing the semantic similarity of top words in a topic, indicating the topic's interpretability.
Perplexity	Measure of how well a model predicts a sample, with lower values indicating better predictive performance.
Dirichlet Prior	Prior distribution in Bayesian models like LDA that controls the sparsity of topic and word distributions through parameters α and β.
Variational Inference	Approximation method for estimating complex posterior distributions in models like LDA by optimizing a simpler distribution.

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Term	**Definition**
Hyperparameters	Parameters defining the behavior of the learning algorithm itself, such as α and β in LDA, influencing topic and word distribution sparsity.
Grid Search	Method for hyperparameter optimization that systematically trains models with different parameter combinations to find the best-performing set.
Coherence Value (CV)	Specific coherence metric combining several measures, including Normalized Pointwise Mutual Information (NPMI), to assess semantic similarity of top words within topics.
NPMI	Normalized Pointwise Mutual Information. Measure of association between two words normalized between -1 and 1, indicating the strength of their co-occurrence.
Generative Model	Statistical model explaining data generation through a probabilistic process involving observed and latent variables, such as LDA.
Posterior Distribution	Probability distribution of latent variables given observed data and prior distributions, representing updated beliefs after data observation.
Topic Proportion	Proportion of each topic within a document, indicating how much each topic contributes to the document's content.
Word Distribution	Probability distribution of words within a topic, indicating how likely each word is to appear in that topic.
Latent Variable	Variables not directly observed but inferred from the data, such as topics and topic proportions in LDA.
Coherence Score	Measure of the semantic similarity of top words in a topic, used to evaluate the quality of topics generated by models like LDA.

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Term	**Definition**
Cross-Validation	Statistical method to estimate the performance of machine learning models by training and testing them on different data subsets.
Word Co-occurrence	The frequency with which two or more words appear together within a specified context in the corpus, used to determine semantic similarity. For example, in climate risk analysis, high co-occurrence of words like "flood" and "damage" indicates a strong association between these terms.

Table A2: List of climate change white papers for transition and physical risk

Year	Source	Title	Transition	Physical
2000	IPCC	Methodological and Technological Issues in Technology Transfer	Entire	
2001	IPCC	IPCC Synthesis Report 2001 (AR3)	302-354p	
2001	IPCC	Climate Change 2001: Impacts, Adaptation, and Vulnerability		Entire
2005	IPCC	IPCC Special Report: Carbon Dioxide Capture and Storage	Entire	
2007	IPCC	IPCC Synthesis Report 2007 (AR4)	55-70p	
2007	IPCC	Climate Change 2007: Impacts, Adaptation, and Vulnerability		Entire
2011	IPCC	IPCC Special Report: Renewable Energy Sources and Climate Change Mitigation	Entire	
2012	IPCC	IPCC Special Report: Managing the Risks of Extreme Events and Disasters to Advance Climate Adapt.		Ch. 2-4
2014	IPCC	IPCC Synthesis Report 2014 (AR5)	75-112p	
2014	IPCC	Climate Change 2014: Impacts, Adaptation, and Vulnerability		Part A & B
2015	Government Offices of Sweden	Sweden's Third National Communication on Climate Change		Ch. 5
2019	IPCC	IPCC Special Report: Global Warming of 1.5°C	Ch. 2 & 4	Ch. 3
2019	IPCC	IPCC Special Report: Climate Change and Land		Ch. 1-5
2019	IPCC	IPCC Special Report: The Ocean and Cryosphere in a Changing Climate		Entire
2020	IMF	The Effects of Weather Shocks on Economic Activity: What Are the Channels of Impact?		Entire
2020	McKinsey Global Institute	Climate Risk and Response: Physical Hazards and Socioeconomic Impacts		Entire
2020	SNS Economic Policy Council	Swedish Policy for Global Climate: Report 2020	Entire	
2021	IPCC	Climate Change 2021: The Physical Science Basis		Ch. 11
2022	IPCC	Climate Change 2022: Impacts, Adaptation, and Vulnerability	Ch. 17-18	Ch. 1-3, 13, 16
2022	IPCC	Climate Change 2022: Mitigation of Climate Change	Entire	
2022	Government Offices of Sweden	Sweden's Adaptation Communication		Entire
2023	IPCC	IPCC Synthesis Report (AR6)	Entire	
2023	Swedish Climate Policy Council	Report 2023	Entire	
2023	Government Offices of Sweden	Sweden's Eighth National Communication on Climate Change	Ch. 1-5, 7	Ch. 6

Note: This table reports the year of publication, source, title of the list of texts used to construct the physical and transition risk seed word lists. List of acronyms: IPCC, Intergovernmental Panel on Climate Change; IMF, International Monetary Fund. The selection criteria and methodologies follow those chosen from the use by Bua et al. (2022) and Engle et al. (2020).

Table A3: Swedish Climate Risk Seed Words and the Original English Words

	Swedish Words Translated	**English Original Words**
$\mathcal{S}_t \in$	{ klimatförändring, koldioxid, hållbar utveckling, klimatpolitik, utsläppsminskning / minska utsläpp / minskning av utsläpp, förnybar energi, klimatrisk, vindkraft, växthusgasutsläpp, klimattålig, parisavtalet, energiförsörjning, utsläppsrätt, klimatmål, klimatpolitiska rådet, global uppvärmning, globala utsläpp, energieffektivitet, kärnkraft, klimatåtgärd, klimatomställning / grön omställning, energibehov, energipolitik, grön teknik, koldioxidinfångning / carbon capture, energiteknik, vindturbin, kyotoprotokollet, klimatpåverkan, miljöpåverkan, hållbarhetsmål, global temperatur, solenergi, hållbar utveckling, ipcc rapport, EU klimatmål, nettonollutsläpp, elekrifiering, utsläppspris, miljödepartementet, fossilt bränsle, vattenkraft, växthuseffekten, grön infrastruktur, koldioxidkoncentration, grön industri, biodrivmedel, elbil, koldioxidlagring, energilagring }	climate change, carbon dioxide, sustainable development, climate policy, emission reduction, renewable energy, climate risk, wind energy, greenhouse emission, climate resilient, paris agreement, energy supply, emission allowance, climate target, climate policy council, global warming, global emission, energy efficiency, nuclear power, climate action, climate change mitigation, climate transition, energy demand, energy policy, green technology, carbon dioxide capture, energy technology, wind turbine, kyoto protocol, climate change impact, environmental goal, global temperature, solar energy, emission trading, ipcc special report, eu green deal, zero emission, electricity generation, emission pricing, ministry climate, fossil fuel, hydro energy, greenhouse gases/effect, green infrastructure, co2 concentration, green industry, biogas, electric vehicle, capture storage, electricity storage
$\mathcal{S}_p \in$	{ klimatpåverkan / påverkan på klimat, klimatflykting, klimatmigration / klimatmigranter / klimatrisk, koldioxidavtryck, skörd, degradering, ökenbildning, naturkatastrof, torka, ekosystem, utsläppsscenario, miljö, miljörelaterade, utsatthet för översvämning, extremväder / extremt väder / väderkatastrof / extrema väderförhållanden, översvämning, skogsbrand / skogsbränder, sötvattens ekosystem, global miljö, global temperatur, global uppvärmning, skogsavverkning, risk, värmebölja, kraftig nederbörd, hög temperatur, extrem påverkan, ökad risk, ökad temperatur, markdegradering / degradering av land / miljödegradering, marina ekosystem, mitigering, naturresurs, havsförsurning, polaris / arktis / antarktis / nordpolen / sydpolen, stigande havsnivå, biologisk mångfald, kustnära ekosystem, storm / tromb / orkan / tyfon / cyklon / stormutveckling, stormvåg, temperaturhöjning / temperaturökning, träddödlighet, tropisk cyklon, vattenresurs / vattenförsörjning, grundvatten, väderhändelse, korallrev, väderchock }	climate effect, climate refugee, climate risk, carbon footprint, crop yield, degradation, desertification, natural disaster, drought, ecosystem, emission scenario, environment, environmental, exposure vulnerability, extreme weather, extreme weather event, flood, forest fire, freshwater ecosystem, global environmental, global temperature, global warming, deforestation, hazard, heat wave, heavy precipitation, high temperature, impact extreme, increase risk, increase temperature, land degradation, marine ecosystem, mitigation, natural resource, ocean acidification, polar ice, polar region, sealevel rise, biological diversity, coastal ecosystem, storm, storm surge, temperature increase, tree mortality, tropical cyclone, water resource, water supply, weather event, coral reef, weather shock

Note: The English list represents the 50 most important terms identified through TF-IDF analysis of authoritative papers. The Swedish list contains more terms because variations and synonyms of the English words were included to better capture the contexts.

Text preprocessing

The preprocessing of textual data is a fundamental step in the development of effective topic models, significantly influencing the quality and interpretability of the resulting analyses. Given the extensive nature of the dataset, the preprocessing workflow was carefully structured to address linguistic nuances and computational considerations.

Initial Article Filtering

At the initial stage of data collection, I encountered numerous news articles that were essentially sales commercials for cars, often highlighting their CO2 emissions. These articles were extracted due to the presence of "CO2" as a search token. However, these articles did not provide meaningful insights related to climate risk. As a result, news articles mentioning the 10 most sold gasoline and diesel cars in Sweden 2023 (Volvo, Volkswagen, Kia, Toyota, Audi, BMW, Mercedes, Skoda, Peugeot, Ford) were excluded from the analysis (Sweden, 2023). This decision does introduce some bias, as it may exclude some news explicitly mentioning these car brands in the context of electric vehicles, but it mostly reduces noise in the data.

Articles containing fewer than 50 words were excluded to ensure that only sufficiently substantive texts were included in the analysis. Similarly, articles exceeding 2000 words were excluded to prevent disproportionately long texts from dominating the topic distributions. A total of 23,957 articles (17.37%) were removed from the "Transition" corpus, reducing it from 137,931 to 113,974 articles (23,491 under 50 words, 466 over 2,000 words). Similarly, 21,018 articles (21.82%) were removed from the "Physical" corpus, reducing it from 96,304 to 75,286 articles (20,807 under 50 words, 211 over 2,000 words). This filtering ensures that only texts of substantive length are included while preventing overly long articles from disproportionately influencing topic distributions, a critical step for robust LDA modelling. The large number of articles with fewer than 50 words is primarily due to copyright reasons, where some articles are randomly abridged after 20 words.

Token Processing and Text Normalization

Initially, all characters within the corpus were converted to lowercase to ensure uniformity and mitigate variability introduced by case distinctions. This standardization is necessary for reducing the dimensionality of the dataset and preventing redundant representations of identical terms. Following this transformation, tokens classified as either excessively common or exceedingly rare were systematically excluded. The common tokens comprised both Swedish and English stopwords—functional words that contribute minimally to the semantic content of the texts, such as "att" (to), "för" (for), and "men" (but). These stopwords were obtained from collections compiled by peers and made publicly accessible[8].

Their high frequency across the entire corpus made them non-informative, potentially obscuring more salient terms that contribute to the identification of distinct topics. Conversely, tokens appearing five times or fewer across all documents were removed to mitigate noise and eliminate irrelevant information that could detract from the model's ability to discern coherent thematic structures. Additionally, the most common

[8]Access the Swedish stopwords list at: `https://github.com/stopwords-iso/stopwords-sv`

Swedish first and last names were removed from the corpus to prevent personal names from skewing the topic distribution and introducing bias into the model. This step ensures that the analysis remains focused on the thematic content rather than on individual identities, which are peripheral to the study's objectives. [9]

The subsequent phase involved the linguistic normalization of the remaining tokens through lemmatization, a process that maps inflected forms of a word to its canonical lemma. This technique derived the semantic integrity of terms while reducing variability, thereby enhancing the model's ability to group semantically similar terms and accurately identify key topics. For instance, the words "klimatförändringar" (climate changes), "klimatförändringarnas" (from climate changes), and "klimatförändringarna" (the climate changes) are all reduced to the lemma "klimatförändring" (climate change). By combining these different forms of a word into a single lemma, lemmatization ensures that variations of a word do not fragment the analysis, allowing the topic model to recognize and group related concepts within the corpus more effectively. To achieve this, tools pre-programmed to analyze Swedish were used.

A bigram and trigram model was employed to capture multi-word expressions that convey specific meanings beyond individual tokens. This process involves identifying frequently co-occurring pairs and triplets of words, which are then treated as single terms within the corpus. For instance, phrases such as "global uppvärmning" (global warming) and "förnybar energi" (renewable energy) are recognized as distinct entities rather than separate words, thereby increasing the semantic richness of the dataset. Similarly, a trigram like "klimatrelaterade ekonomiska risker" (climate-related economic risks) preserves the specific contextual relationship between these terms. These multi-word expressions enhance the depth and accuracy of the topic modelling process by maintaining the contextual relationships between related concepts.

However, the inclusion of n-grams can also lead to an increase in the dimensionality of the dataset, as each new n-gram represents an additional feature, potentially exacerbating the curse of dimensionality (Feldman and Sanger, 2007). To balance the benefits of capturing contextual information with the computational challenges posed by increased dimensionality, thresholds for minimum co-occurrence frequencies and association strength were established. Specifically, only word pairs (bigrams, trigrams) appearing at least 20 times in the corpus were considered, and a threshold of 100 was applied to ensure a strong association between words. This ensures that the model focuses on relevant multi-word expressions without being overwhelmed by an excessive number of features, thereby maintaining computational efficiency and model performance.

Concurrently, the corpus was cleansed of all non-alphabetic characters, including digits, whitespace, and punctuation, to concentrate the analysis solely on meaningful textual content. To enhance computational efficiency and reduce the sparsity of the dataset, a final filtering step was implemented to remove tokens that were either excessively rare or too common across the corpus. Specifically, tokens appearing in fewer than 50 documents or more than 50% of the documents were excluded. This dual removal strategy ensures that only terms with moderate frequency, which are widely shared among articles, remain in the vocabulary. As a result, this approach increases the proportion of meaningful terms within each document, improving computational efficiency during the topic modelling process.

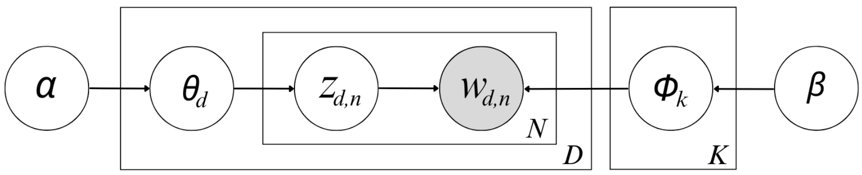
[9] List of common Swedish names used available at: `https://github.com/peterdalle/svensktext/tree/master/namn`

Posterior Distribution Estimation and Inference in LDA

The LDA model is built on a hierarchical generative process, where observed variables ($w_{d,n}$) represent the words in the corpus. These observed words are linked to latent variables that define the structure of topics and their distribution. This is illustrated in Figure A1, with the shaded circle representing the observed variables and the unshaded representing latent variables. The generative process can be described as follows:

At the topic level (K), the hyperparameter β shapes the Dirichlet prior to which each topic's word distribution (ϕ_k) is sampled. This determines the diversity of words within a topic, controlling the specificity or breadth of the topics. At the document level (D), for each document d, the topic distribution (θ_d) is drawn from a Dirichlet prior parameterized by α. At the word level (N), for each word position n in document d, a topic $z_{d,n}$ is sampled from the document's topic distribution (θ_d). The word $w_{d,n}$ is then generated from the topic-specific word distribution ($\phi_{z_{d,n}}$).

Figure A1: A graphical representation of the generative process in Latent Dirichlet Allocation



Posterior Distribution Objective

The objective of LDA is to estimate the posterior distribution of the latent variables (ϕ, θ, z) given the observed words w and the hyperparameters α and β:

$$p(\phi, \theta, z \mid w, \alpha, \beta) = \frac{p(w, z, \theta, \phi \mid \alpha, \beta)}{p(w \mid \alpha, \beta)}.$$

This posterior distribution represents the updated beliefs about the latent variables after observing the data. It includes the word distributions for each topic (ϕ_k), the topic distributions for each document (θ_d), and the topic assignments for each word ($z_{d,n}$). The numerator captures the joint probability of both the observed words and the hidden variables, while the denominator normalizes this by accounting for the overall likelihood of the observed words across the corpus. This ensures that the result represents a valid probability distribution.

Challenges in Posterior Estimation and Approximation Methods

Estimating the posterior distribution $p(\phi, \theta, z \mid w, \alpha, \beta)$ is computationally challenging due to the high dimensionality and the combinatorial nature of the latent variables. Direct computation requires evaluating the marginal probability $p(w \mid \alpha, \beta)$, which involves summing over all possible configurations of ϕ, θ, and z. This summation grows exponentially with the number of topics and the size of the corpus, rendering it infeasible for practical applications. For a corpus with 100,000 documents, each containing 500 words, and assuming ten topics and a total vocabulary size of 50,000 unique words, the number of possible configurations of the latent variables grows astronomically as $(10^{500})^{100,000} \times 50,000^{10}$. This illustrates the computational infeasibility of direct posterior estimation.

To address this, approximation methods are used. *Variational Bayes* approximates the posterior by defining a set of simpler distributions, each of which is characterized by a set of parameters. These parameters, such as the mean and variance in the case of a Gaussian distribution, determine the shape and characteristics of the distribution. By adjusting these parameters, Variational Inference seeks the distribution that most closely approximates the true posterior. The task is then reframed as an optimization problem, where the goal is to minimize the divergence between the approximated and true posterior. This approach is both scalable and efficient, making it particularly suited for large datasets (Blei et al., 2003). An alternative is Sampling-Based Methods, such as *Gibbs sampling*, which iteratively sample from the posterior by conditioning on the current state of other variables. While effective for smaller datasets, these methods become computationally demanding for high-dimensional problems (Griffiths and Steyvers, 2004).

This study employs *Variational Bayes* to approximate the posterior distribution within the LDA framework. By optimizing the parameters of the variational distributions, this method efficiently estimates the latent variables, including the topic-word distributions (ϕ_k) and document-topic distributions (θ_d). *Variational Bayes* is chosen for its computational efficiency and ability to handle high-dimensional data, enabling the identification of coherent topics and their prevalence across the corpus within a reasonable timeframe. Additionally, *Variational Bayes* effectively scales with the size of the corpus, making it ideal for the large-scale text data typically associated with LDA models. This scalability ensures that the model remains practical and efficient even as the volume of data grows.

Optimization of Hyperparameters in LDA

In LDA, the selection of hyperparameters α and β plays a significant role in effectively modelling the distributions of topics within documents and words within topics. These parameters, corresponding to the Dirichlet distributions for topic distributions per document and word distributions per topic, respectively, have a strong influence on the thematic structure of the model output. The parameter α influences the topic distribution within documents, where each component $\theta_{d,k}$ of the vector θ_d represents the probability of topic k appearing in document d. I will further discuss the relation of $\theta \sim \text{Dirichlet}(\alpha)$, as shown in Figure A2, and the selection of this parameter in more detail. The process for $\phi \sim \text{Dirichlet}(\beta)$ is analogous and follows a similar structure for calculation and selection. The distribution of α is defined by the Dirichlet density function:

$$p(\theta \mid \alpha) = \frac{\Gamma\left(\sum_{i=1}^{K} \alpha_i\right)}{\prod_{i=1}^{K} \Gamma(\alpha_i)} \prod_{i=1}^{K} \theta_i^{\alpha_i - 1},$$

where Γ denotes the Gamma function, and K is the total number of topics. Similarly, the parameter β influences how words are distributed within topics, affecting the granularity and precision of the vocabulary attributed to each topic. It determines the diversity or density of word usage, thereby shaping the detailed description and thematic distinction of each topic.

A symmetric α implies an equal likelihood of any topic being prominent in a document, suitable when no prior knowledge about topic prevalence is available. An asymmetric α allows for varying probabilities, useful if some topics are known to be more prevalent a priori. The choice between symmetric and asymmetric configurations and the specific values within these categories directly affects how topics are represented in documents; higher α values typically lead to a more uniform distribution of topics across documents, while lower values promote sparsity, potentially enhancing the clarity and separation of topics. For β, lower values promote a higher concentration of fewer, more distinctive words within topics, thus enhancing the ability of the model to differentiate between them. Conversely, higher values of β result in each topic having a more extensive and less specific vocabulary.

In the context of news articles, low values for both α and β enhance topic clarity and specificity. Low α sharpens the focus on distinct events within each article, reducing thematic overlap and promoting a clearer separation of topics. Similarly, low β ensures that topics are defined by a tightly focused set of keywords, making it easier to distinguish and interpret specific news themes. This configuration is particularly effective for news datasets where articles are centred around specific, well-defined events or issues. To identify the optimal values for these parameters, I employed a grid search strategy, testing combinations of α values from the set {'symmetric', 'asymmetric', 0.01, 0.05, 0.1, 0.2, 0.5} and β values from {0.001, 0.01, 0.05, 0.1, 0.2, 'auto'}. This approach allowed me to systematically and objectively evaluate the impact of these hyperparameters on the coherence and distinctiveness of topics generated by the LDA model.

Figure A2: Impact of the α Parameter on Dirichlet Distributions in Topic Modelling

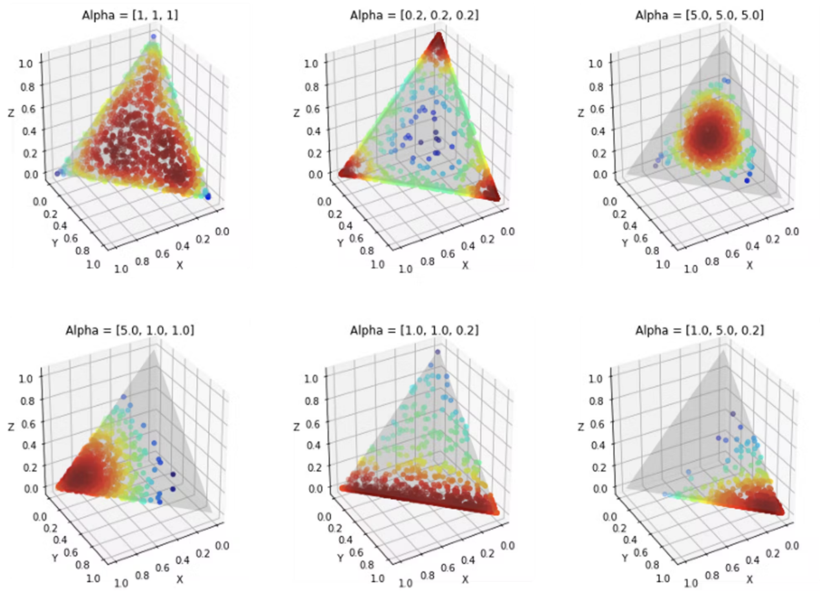


Figure Description: The upper part of the figure illustrates a Symmetric Dirichlet Distribution and the lower part is an Asymmetric Dirichlet Distribution. Each point within the diagrams represents the topic proportion vector θ_d for one of a hypothetical amount of documents, which could be denoted by $d \in \{1, 2, \ldots, 50000\}$. The corners of the triangles, labelled X, Y, and Z, correspond to pure concentrations of the three topics k. A point's proximity to a vertex indicates the dominance of that topic in a document, with points near the centre suggesting a balanced distribution of all topics. This visualization demonstrates how the α parameter impacts the diversity and concentration of topics across documents, providing insight into the effect of different α settings on the thematic structures within the documents.

The 'auto' setting allows the model itself to adjust the α and β parameters based on the data, potentially optimizing model performance dynamically. For this analysis, I utilized a random sample of 10,000 articles from the corpus. Separate grid searches were conducted for each of the two distinct sets of articles; one focused on transition risks articles and the other on physical risks articles.

The evaluation of the grid search was conducted using perplexity and coherence metrics, ensuring a balance between the probabilistic fit of the model and the interpretability of the generated topics. A detailed description of these metrics, the methodology, and their results will be provided in the next section. By systematically adjusting key hyperparameters and analyzing their effects on topic coherence and separation, the grid search process fine-tunes the LDA model to capture the thematic structures within the corpus better. This approach not only ensures the model's alignment with the data but also addresses the issue of LDA's sensitivity to hyperparameter values of α and β. Through this empirical evaluation, the hyperparameter settings that perform the best are selected, with the optimal values identified as:

$$\alpha = 0.01 \quad \text{and} \quad \beta = 0.001$$

Determining the Optimal Number of Topics K

Coherence score

Topic coherence is central for evaluating the interpretability of topics produced by unsupervised models like LDA. By quantifying the semantic similarity among high-probability words within each topic, coherence scores allow researchers to identify topics that are meaningful as opposed to those that are statistical byproducts of the model's inference process. This interpretability is essential because topics generated by unsupervised models aren't validated against a set standard, making it necessary to use metrics that mirror human judgment of quality (Chang et al., 2009; Röder et al., 2015).

The Coherence Value metric (CV), introduced by (Röder et al., 2015), is particularly effective in evaluating topic models due to its alignment with human judgments of topic quality. Among coherence metrics, CV is notable for using Normalized Pointwise Mutual Information (NPMI), which has been shown to provide reliable results across diverse datasets by capturing the association strength between word pairs in a way that is intuitively interpretable and comparable (Lau et al., 2014; Mimno et al., 2011).

NPMI, as a refined version of Pointwise Mutual Information (PMI), adjusts PMI scores to a bounded scale between -1 and 1. This normalization enhances interpretability across word pairs, as values close to 1 indicate a strong association, values near 0 imply independence, and negative values indicate that the words rarely occur together. NPMI is calculated as follows:

$$\text{NPMI}(w_i, w_j) = \frac{\log\left(\frac{P(w_i, w_j)}{P(w_i)P(w_j)}\right)}{-\log P(w_i, w_j)} \tag{5}$$

where:

- $P(w_i, w_j)$ is the probability of words w_i and w_j co-occurring within a defined context.
- $P(w_i)$ and $P(w_j)$ are the individual probabilities of each word.

To compute the coherence score for a topic T, the CV metric averages the NPMI scores across all unique pairs of the top n terms within the topic. Research commonly sets $n = 10$, as studies show this number strikes a balance between interpretability and statistical reliability, with higher coherence scores correlating well with human perceptions of topic quality (Stevens et al., 2012; Röder et al., 2015):

$$\text{coherence}_{CV}(T) = \frac{1}{\binom{n}{2}} \sum_{i \neq j} \text{NPMI}(w_i, w_j) \tag{6}$$

This aggregated score captures the overall semantic coherence of a topic, effectively summarizing how well the high-probability terms semantically support each other. Studies such as those by (Lau et al., 2014) confirm that NPMI-based coherence scores provide a robust proxy for human interpretability, making the CV metric a preferred choice for evaluating topic quality across a range of applications. The CV coherence score typically increases as the model finds more semantically meaningful groupings of words but often reaches a plateau as K increases. This trend generally indicates that adding more topics beyond a certain point does not contribute to significantly higher coherence. The coherence score ranges from 0 to 1, where values closer to 1 represent stronger semantic association among top words within topics. This plateau is an essential indicator in determining the optimal number of topics, as a flattening curve suggests diminishing returns in topic quality with further increases in K.

Perplexity

In addition to topic coherence, perplexity is a widely used measure in natural language processing to assess the predictive power of topic models. Perplexity quantifies how well a model generalizes to unseen data, with lower perplexity values indicating a better fit to new documents. To determine the optimal number of topics K, both CV coherence and perplexity scores are used in a complementary fashion. While CV coherence assesses the semantic interpretability of topics, perplexity evaluates their predictive accuracy, providing a balanced and more holistic approach to model selection. Defined as the inverse probability of the test set normalized by the number of words, perplexity is calculated as follows:

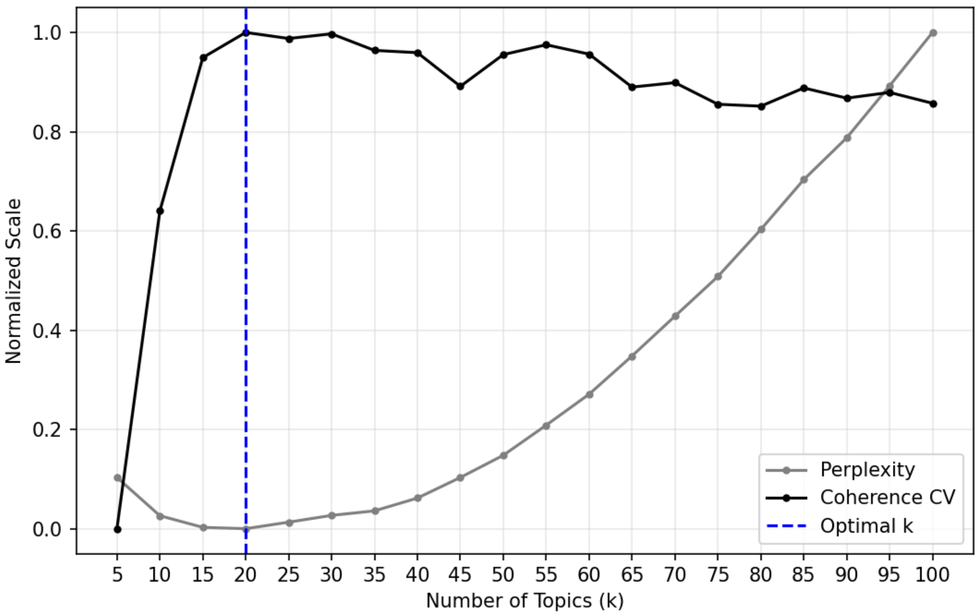
$$\text{perplexity}\,(D) = \exp\left\{-\frac{\sum_{d=1}^{D} \log p\,(w_d)}{\sum_{d=1}^{D} N_d}\right\} \tag{7}$$

Where D represents the set of test documents, $p(w_d)$ denotes the probability of the observed word distribution in document d, and N_d is the number of words in document d. Lower perplexity values indicate a model that more accurately predicts held-out data, making perplexity an essential metric for evaluating the generalizability of topic models (Blei et al., 2003; Griffiths and Steyvers, 2004).

In this study, a grid search over a set of K values (e.g., {5, 10, 15, 20, 25, 30, ..., 100}) was conducted using a random sample of 10,000 articles from the dataset, representing approximately 10% of the corpus per category (transition, physical). For each value of K, both the CV coherence and perplexity scores were computed on the sample, and the final scores were averaged to identify the optimal number of topics. This approach ensures robust results and reduces the risk of overfitting by evaluating model performance across a representative subset of the data.

The optimal K is identified by examining the trends in coherence and perplexity scores: coherence generally increases and then plateaus, whereas perplexity decreases and reaches its lowest score. The point where both curves stabilize, with coherence remaining high and perplexity at its lowest, indicates an appropriate balance between interpretability and generalizability, suggesting the optimal number of topics. A demonstration of this can be seen in Figure A3, which shows the results for estimating K for the transition risk corpus. Additionally, analyses of both the transition risk and physical risk corpora resulted in an optimal number of topics $K = 20$.

Figure A3: Evaluation of LDA Models Across Different k Values



Note: Normalized perplexity and Coherence CV metrics for the transition risk corpus. A lower value of perplexity reflects a model's improved capability to predict unseen data accurately, while a higher Coherence CV value indicates that the model has effectively captured meaningful and coherent topics within the data.

Table A4: Detailed Overview of LDA Hyperparameters: Tested Ranges and Optimal Configurations

Hyperparameter	**Description**	**Optimal Configuration**
num_topics (K)	Number of topics to be extracted, tested across a range. *integer, $k > 0$, tested values: 5, 10, 15, 20, 25, 30, ..., 100*	20
passes	Number of passes through the corpus during training. *integer, $x > 0$*	100
iterations	Maximum number of iterations through the corpus when inferring the topic distribution of a corpus. *integer, $x > 0$*	250
alpha	Dirichlet hyperparameter controlling the document-topic density, tested to optimize topic distribution sparsity. *Options: 'auto', 'asymmetric', 0.01, 0.05, 0.1, 0.2, 0.5*	0.01
beta	Dirichlet hyperparameter controlling the term-topic density, tested to adjust the influence of term frequency on topic formulation. *Options: 'auto', 'asymmetric', 0.001, 0.01, 0.05, 0.1, 0.2*	0.001

Note: The configurations presented in this table were derived from extensive testing involving a range of potential values for each parameter to ensure robust model performance while minimizing overfitting and underfitting. The settings were selected based on their ability to optimize the coherence and perplexity of the model across diverse datasets.

Selection and Interpretation of Topics

To effectively analyze the thematic content of the document corpus, I employed LDA to infer underlying topics. The primary objective was to identify topics that are not only prominent across the corpus but also broad enough to be relevant and semantically coherent. This ensures that the topics are significant in terms of their prevalence, meaningful in their content, and applicable for enriching the understanding of the subject matter, thereby contributing valuable insights to the analysis. Tables A5 and A6 provide a comprehensive overview of the inferred topics, including their prevalence, coherence scores, and the top 20 associated words. I calculated the *prevalence* of each topic, which indicates how dominant a topic is within the entire corpus. Topic prevalence is measured as the proportion of documents where a particular topic is the most significant. Mathematically, the prevalence P_k for topic k is defined as:

$$P_k = \frac{\sum_d \theta_{d,k}}{D} \times 100 \tag{8}$$

where:

- $\theta_{d,k}$ is the probability of topic k in document d.
- D is the total number of documents in the corpus.

To evaluate the utility of each topic for our research, the *coherence* of each topic was assessed to determine its semantic interpretability. As described in the section on Coherence score, topic coherence measures the degree of semantic similarity between the high-scoring words within a topic, providing insight into how meaningful and distinguishable the topic is (Röder et al., 2015; Mimno et al., 2011). Higher coherence scores indicate that the words within the topic are more semantically related, enhancing the topic's interpretability and relevance (Lau et al., 2014). Both their prevalence and coherence scores guided the selection of topics for detailed analysis and, importantly, their breadth and relevance to the research objectives:

High Prevalence and High Coherence: Topics that are both widely represented in the corpus and have coherence scores above 0.4 were prioritized. These topics are likely to be significant and offer clear thematic insights. However, extremely high prevalence might mean that the topic includes very common or generic words that appear frequently across many documents. This can reduce the distinctiveness of the topic to uniquely characterize segments of the corpus, making it less useful for detailed analytical purposes.

High Prevalence but Low Coherence: Some topics exhibited high prevalence but had coherence scores below the 0.4 threshold. These topics often contained common words that are frequently used across documents but do not form a cohesive theme. An example is topic 7 and 18 in Table A6, where I was unable to identify a specific topic. These topics were not included in the analysis.

Low Prevalence but High Coherence: Topics with lower prevalence but high coherence were considered based on their relevance to my research objectives. These topics, although not dominant, may represent specialized or niche areas of interest. An example of being too niche is found in Topics 10 and 14 of Table A5, which focus on aviation and deforestation in Brazil. Although these topics are highly coherent and relevant to specific issues, they were not prioritized for detailed analysis as they did not sufficiently align with the study's broader research objectives.

For each selected topic, I analyzed the top 20 words with the highest probability of association to understand the underlying themes. This involved examining the frequency and co-occurrence patterns of these words within the corpus. When the top words did not sufficiently reveal the topic's nature, I examined sample documents where the topic was predominant. This qualitative analysis allowed me to assign descriptive labels to the topics and confirm their broad relevance and utility for my study. This dual approach of quantitative metrics and qualitative assessment ensures a robust and detailed understanding of each topic (Faccini et al., 2023).

Table A5: Summary of Physical Risk Topics

Topic nr.	Topic Theme	Coherence	Prevalence (%)	Top Words
0	Weather extremes	0.6191	17.4827	drabba, översvämning, orkan, område, miljon, kraftig, stad, myndighet, regn, rapportera, vatten, storm, vänta, hem, skada, nå, sakna, väg, uppge, evakuera
4	Meteorological updates and alerts	0.7166	8.2260	smhi, regn, vänta, temperatur, södra, snö, väg, hel, vecka, grad, varning, vind, risk, kraftig, norrland, natt, norra, håll, väder, helg
6	Fire emergencies and related rescue efforts	0.6264	8.1850	bränd, område, brande, räddningstjänst, skada, vatten, hus, drabba, väg, hem, evakuera, rasa, skogsbränd, skogsbrand, kraftig, stad, vind, hel, rapportera, tid
2	Social and political issues	0.3498	7.8421	barn, fråga, tid, skriva, kvinna, hel, tycka, veta, egen, politisk, tänka, tal, president, liv, folk, börja, politik, hålla, trump, handla
3	Global environmental policy and agreements	0.5353	6.4930	utsläpp, global, eu, minska, mål, fråga, avtal, öka, rapport, parisavtal, möte, nå, klimat, grad, global uppvärmning, usa, regering, hålla, internationell, fattig
11	Lifestyle or travel-related themes	0.3943	6.0901	hel, tid, resa, börja, timme, plats, krona, a, hus, hålla, väg, spela, bo, hotell, vecka, familj, just, åka, tänka, par
16	Global warming	0.5412	5.6558	temperatur, öka, varm, grad, värmebölja, varmare, luft, sommar, risk, extrem, grada, värm, jord, torka, påverka, klimat, minska, drabba, barn, hel
9	Environmental policies regarding emissions	0.4491	4.9717	utsläpp, minska, öka, koldioxid, använda, miljö, regering, ton, bygga, kräva, fråga, hel, klimat, exempel, köra, skatt, koldioxidutsläpp, mål, förslag, bränsle
15	Governance, environmental and economic policies	0.4040	4.7738	regering, öka, företag, skog, fråga, förslag, kärnkraft, utveckling, minska, bygga, ekonomisk, möjlighet, kräva, miljö, skapa, politik, tid, skriva, exempel, mål
13	Business practices and sustainability	0.4110	4.5347	företag, bolag, kund, produkt, minska, använda, öka, hållbar, miljon, vin, krona, marknad, olik, hel, verksamhet, global, information, köpa, egen, mål

Continued on next page

Table A5 – continued from previous page

Topic ID	Category	Coherence	Prevalence (%)	Most Important Words
1	Municipal preparedness and flood management	0.4259	3.9662	kommun, vatten, översvämning, risk, område, öka, drabba, sommar, miljon, problem, beredskap, krona, bygga, räddningstjänst, mark, regering, hel, msb, myndighet, skada
17	Marine, Biodiversity and conservation	0.3952	3.5066	vatten, hav, art, jord, fisk, djur, natur, hel, hitta, område, tal, växt, olik, gammal, tid, börja, växa, leva, plats, hålla
12	Agriculture and food production	0.5970	3.5026	mat, kött, äta, ekologisk, öka, djur, jordbruk, minska, odla, pris, skörd, konsument, producera, köpa, livsmedel, produktion, använda, hel, miljö, välja
19	Economic topics, pricing and market trends	0.3577	3.4987	pris, öka, stiga, olja, krona, vänta, bolag, amerikansk, låg, miljon, månad, jämföra, vecka, fartyg, tillväxt, miljard krona, stark, marknad, minska, usa
7	Antarctic Changes and Sea Level Rise	0.4715	3.0192	art, is, snabb, minska, glaciär, rapport, jord, studie, hav, öka, klimatförändring, område, klimat, stiga, antarktis, miljon, meter, vatten, påverka, hel
8	Urban development in China	0.3729	2.5144	kin, stad, miljon, kinesisk, bygga, peking, område, regering, myndighet, vatten, kinas, krona, kina, företag, plats, hel, tid, problem, luft, huvudstad
18	Hurricane Katrina and Urban Resilience	0.5166	2.3125	stad, vatten, new, stiga, översvämning, new orleans, bygga, meter, hus, område, drabba, orkan, vattennivå, hel, bo, vänta, börja, väg, tid, nära
10	Aviation and transportation	0.5322	1.2884	plan, flygplats, flygplan, tid, burma, flygbolag, flyga, stad, resa, plats, ombord, passagerare, skriva, flyg, uppgift, pilot, grund, resenär, arlanda, drabba
14	Environmental issues and deforestation in Brazil	0.5755	1.1237	brasilien, regnskog, skog, amazoe, avskogning, greta thunberg, bränd, palmolja, amazonas, öka, hel, miljon, brasili, brasiliansk, bolsonaro, president, klimat, mark, skriva, tid
5	Traffic and urban environmental assessments	0.3628	1.0135	trafik, träd, påverka, väg, skog, klocka, bedöma, varning, påverkan, miljon, problem, ämne artikel, län, översvämning, gran, bolag, s textrobot, bild, båda riktning, händels uppge

Table A6: Summary of Transition Risk Topics

Topic nr.	Topic Theme	Coherence	Prevalence (%)	Most Important Words
9	Corporate Development and Sustainability	0.4896	8.6994	bolag, företag, kund, krona, öka, miljard, marknad, aktie, verksamhet, information, cirka, utveckling, miljon, utveckla, produkt, ytterlig, hållbar, investering, mål, bygga
7	Unrecognized	0.5263	7.9632	vatten, barn, temperatur, hel, klimatförändring, öka, tid, börja, varm, område, drabba, klimatförändringarna, påverka, sommar, grad, jord, översvämning, svår, risk, varmare
18	Unrecognized	0.3368	7.3587	hel, stad, tid, skog, hålla, tal, plats, börja, gammal, tänka, just, fråga, vecka, tycka, egen, folk, bränd, bild, barn, liv
2	Political Dynamics and Environmental Policy	0.5	7.1999	parti, regering, förslag, politik, miljöparti, skatt, fråga, eu, höja, val, politisk, jobb, grön, krona, miljard, öka, socialdemokrat, ekonomisk, mp, väljare
0	Swedish Political Dynamics and Campaigns	0.7303	7.092	regering, parti, fråga, val, politik, s, moderat, riksdag, tycka, väljare, politisk, miljöparti, stefan löfven, socialdemokrat, m, allians, borgerlig, löfven, tid, liberal
6	Global Diplomacy and Environmental Activism	0.4661	6.0137	greta thunberg, eu, skriva, möte, president, fråga, usa, trump, hålla, vecka, fredag, regering, tid, avtal, lämna, delta, amerikansk, plan, tal, thunberg
13	International Climate Agreements	0.507	5.5969	utsläpp, minska, koldioxid, klimat, global, eu, öka, jord, mål, grad, fråga, rapport, växthusgase, parisavtal, kräva, global uppvärmning, politik, klimatförändring, snabb, tid
11	Wind Energy Systems and Infrastructure	0.4528	5.1556	bygga, vindkraft, kommun, vindkraftverk, regering, miljard, företag, energi, öka, hel, krona, producera, bostad, anläggning, elnät, område, elproduktion, hus, kraftnät, planera
3	Swedish Climate Policies	0.4144	4.8941	regering, utsläpp, minska, mål, öka, krona, stad, miljon, förslag, åtgärd, nå, miljard, miljö, klimatmål, koldioxid, ton, kräva, låg, införa, innebära

Continued on next page

Table A6 – continued from previous page

Topic ID	Category	Coherence	Prevalence (%)	Most Important Words
19	Global Development and Sustainability Goals	0.4023	4.8529	global, öka, miljard, utveckling, företag, regering, minska, mål, ekonomisk, eu, fattig, utsläpp, fråga, hållbar, avtal, tillväxt, internationell, miljon, kin, pengar
12	Energy Transition Policies	0.566	4.6949	kärnkraft, reaktor, regering, bygga, förnybar, vindkraft, energi, energipolitik, reglering, öka, fråga, industri, kraftverk, elproduktion, politisk, avveckla, stänga, tid, tysk, investering
14	Sustainable Transport and Infrastructure	0.3919	4.4703	utsläpp, minska, öka, använda, skog, kommun, ton, kräva, transport, hel, utveckling, bygga, väg, koldioxid, bränsle, hållbar, exempel, mål, energi, möjlighet
16	Economic Trends and Market Dynamics	0.4803	4.4186	krona, miljon, pris, öka, miljard, låg, stiga, bolag, kvartal, resultat, jämföra, skatt, månad, vänta, elpris, minska, höja, cirka, räkna, efterfrågan
15	Regulatory Compliance and Environmental Law	0.3726	4.3457	regering, företag, myndighet, fråga, förslag, område, tillstånd, krav, verksamhet, utredning, anse, kommun, innebära, skriva, lag, bolag, använda, stat, domstol, kräva
1	International Trade and Economic Strategies	0.453	3.6956	kin, usa, amerikansk, president, öka, trump, miljon, miljard, olja, global, minska, kol, kinesisk, fråga, ekonomisk, bid, obama, företag, samtidig, vänta
8	National Aviation and Taxes	0.4769	2.9902	s, krona, regering, resa, tåg, köra, flyga, motor, flygplats, flyg, arlanda, tid, plan, fråga, mil, pris, flygskatt, flygbolag, välja, volvo
5	Electric Vehicle Market and Policy Developments	0.4226	2.8577	krona, elbil, företag, regering, köpa, betala, elbila, jobb, pengar, öka, saab, pris, hel, köra, kostnad, ladda, fråga, miljard, miljon, batteri
10	Consumer Behavior and Sustainable Practices	0.32	2.8313	företag, använda, produkt, köpa, krona, handla, kläder, miljö, fråga, tid, exempel, egen, vatten, hel, minska, kund, öka, börja, konsument, miljon
4	Sustainable Agriculture and Food Systems	0.5099	2.5699	mat, kött, äta, minska, ekologisk, öka, miljö, fond, jordbruk, välja, djur, konsument, hållbar, använda, livsmedel, odla, olik, fråga, producera, produkt

Continued on next page

Table A6 – continued from previous page

Topic ID	Category	Coherence	Prevalence (%)	Most Important Words
17	Energy Investments in Germany	0.4862	2.2996	tyskland, vattenfalla, bolag, tysk, regering, miljard, pris, utsläpp, företag, utsläppsrätt, krona, sälja, öka, elpris, stat, koldioxid, affär, minska, köpa, statlig

Appendix B: Financial and Asset Pricing Methods

Data Cleaning Procedures

In preparing the dataset for analysis, data cleaning procedures were implemented to ensure the robustness and reliability of the findings. First and foremost, numerous large companies issue multiple classes of shares (e.g., Class A, Class B, and preferred shares). Prices for different share classes within the same company generally move in tandem, and key financial ratios are nearly identical. This redundancy may skew the models' factors by giving these observations disproportionate influence. To mitigate this, only one share class per company was kept. The share class with the fewest available data points was eliminated; if the data were comparable, the class with the highest trading volume was dropped. Companies with 100% missing values in any key variable were excluded from the study. Additionally, a threshold of 80% missing data across all variables was established; firms exceeding this limit were removed. This threshold was particularly important for emission data, which had significant missing values.

Although this approach results in the exclusion of newly entering firms, such exclusion is justified within the context of climate risk assessment. Climate risk is a long-term phenomenon, and capturing its effects requires consistent and comprehensive data over extended periods (Dietz et al., 2016). Newly listed companies may exhibit volatile financial behaviours and unusual responses to market conditions as they establish their market presence, which can introduce noise and distort the analysis of long-term risk factors (Fama and French, 2004a). This approach aligns with established statistical methodologies, as the complete absence of data for critical variables renders a firm unsuitable for the Fama French factor models (Fama and French, 1993, 2004b).

In addition, forward filling was employed for weekends and holidays to ensure continuity in the dataset. Furthermore, stock splits were managed by identifying and correcting outliers, thereby maintaining data accuracy. As a result of these data-cleaning procedures, the final dataset comprises 497 firms, each meeting the criteria for data completeness and continuous market presence. This refined dataset ensures that the subsequent examination of climate-related financial impacts is both credible and scientifically sound, providing a robust foundation for empirical analysis.

Table B1: Financial and Economic Variables for Market Analysis

Variable	**Description**	**Source**
Risk free-rate	1-month Swedish Treasury bill rate annualized by dividing by 360, used as a risk-free benchmark	Sveriges Riksbank
Yield Curve	The spread between the 3-month Treasury bill rate and the 2-year government bond yield, a proxy for economic conjuncture and market expectations on growth and inflation	Sveriges Riksbank
Economic Policy Uncertainty Index	An index quantifying economic policy uncertainty based on media coverage and legislative actions	Economic Policy Uncertainty
OMX Stockholm All-Share Index	A comprehensive index tracking the performance of the Swedish equity market	Nasdaq database
Market capitalization	Computed as the bid price times the number of shares outstanding	Eikon Refinitiv
Book Value per Share	The firm's book value divided by its number of shares	Eikon Refinitiv
Total Assets	The sum of all assets owned by a firm	Eikon Refinitiv
Operating Expenses	Day-to-day operational costs excluding production expenses, indicating efficiency	Eikon Refinitiv
Direct Emissions Intensity – Scope 1	Direct CO_2 and CO_2 equivalent emissions (in thousand metric tonnes)	Eikon Refinitiv
Indirect Emissions Intensity – Scope 2	Indirect CO_2 and CO_2 equivalent emissions (in thousand metric tonnes) from purchased energy	Eikon Refinitiv
Return on Assets	Operating income before depreciation divided by average total assets over the two most recent periods	Eikon Refinitiv
R&D	Research and development expenses as a fraction of sales, indicating innovation intensity	Eikon Refinitiv
E-Score	A weighted environmental performance rating on a 1–100 scale based on reported data	Eikon Refinitiv
ESG Score	An overall score (1–100) integrating self-reported environmental, social, and governance performance	Eikon Refinitiv
log(Size)	The logarithm of market capitalization	Eikon Refinitiv

Construction of Factors

To construct the Fama-French factors, portfolios are organized to serve as explanatory variables for asset pricing models. These factors are derived by applying specific financial and market data to categorize and evaluate companies. This process begins by sorting companies into portfolios based on their size, book-to-market ratios (B/M), operating profitability, and investment profiles. For the Fama-French Three-Factor Model (FF3), companies are divided into groups of 'small' or 'big' based on market capitalization, and further sorted by 'low', 'neutral', or 'high' book-to-market ratios. The size factor (SMB) captures the differential returns between small and big firms, while the value factor (HML) measures the returns between high and low book-to-market firms. The Carhart Four-Factor Model introduces a momentum factor (MOM), which analyzes the performance trends of stocks, distinguishing between past winners and losers based on their returns. The Fama-French Five-Factor Model (FF5) extends FF3 by including two additional factors: operating profitability (RMW) and investment (CMA). These are calculated by grouping firms into portfolios based on robust versus weak profitability and conservative versus aggressive investment strategies. The construction formulas are presented here:

Fama-French Three-Factor Model (FF3)

Size Factor ($\mathbf{SMB}_{B/M}$): The SMB (Small Minus Big) factor captures the size effect on excess returns. It is calculated as the difference in simple average returns between firms with small and big market capitalization. Specifically, market capitalization is derived from the *Number of Shares Outstanding* multiplied by the *Closing Bid Price.*

$$\text{SMB}_{B/M} = \frac{S/L + S/N + S/H}{3} - \frac{B/L + B/N + B/H}{3}$$

Where: S and B denote Small and Big firms, respectively. L, N, and H denote Low, Neutral, and High B/M ratios, respectively.

Value Factor (HML): The HML (High Minus Low) factor represents the value effect, distinguishing between high and low B/M ratio firms. The B/M ratio is computed using *Book Value per Share* and *Closing Bid Price.*

$$\text{HML} = \frac{S/H + B/H}{2} - \frac{S/L + B/L}{2}$$

Where: S and B denote Small and Big firms, respectively. H and L denote High and Low B/M ratios, respectively.

Carhart Four-Factor Model

Momentum Factor (MOM): Based on Carhart (1997), the momentum factor captures the tendency of stocks with high past returns (winners) to continue performing well, and those with low past returns (losers) to underperform. Momentum is calculated using the *Closing Bid Price* to determine past returns.

$$\text{MOM} = \frac{S/Wi + B/Wi}{2} - \frac{S/Lo + B/Lo}{2}$$

Where: S and B denote Small and Big firms, respectively. Wi and Lo denote Winners and Losers, respectively.

Fama-French Five-Factor Model (FF5)

The FF5 model extends the FF3 by incorporating two additional factors: profitability and investment. These factors are constructed using *Operating Expenses*, *Net Revenues*, and *Total Assets*. **Size Factor ($\mathbf{SMB}_{FF5}$):** The SMB_{FF5} factor integrates three sub-factors: $\text{SMB}_{B/M}$, SMB_{OP} (Operating Profitability), and SMB_{INV} (Investment). Each sub-factor is calculated by sorting firms based on size and the respective second sorting variable.

$$\text{SMB}_{FF5} = \frac{\text{SMB}_{B/M} + \text{SMB}_{OP} + \text{SMB}_{INV}}{3}$$

Where: $\text{SMB}_{B/M}$, SMB_{OP}, and SMB_{INV} represent size factors based on Book-to-Market, Operating Profitability, and Investment, respectively.

Operating Profitability Factor (RMW): The Robust Minus Weak (RMW) factor captures differences in operating profitability. Profitability is assessed using *Operating Expenses* and *Net Revenues* to compute operating profitability.

$$\text{RMW} = \frac{S/R + B/R}{2} - \frac{S/W + B/W}{2}$$

Where: S and B denote Small and Big firms, respectively. R and W denote Robust and Weak profitability, respectively.

Investment Factor (CMA): The Conservative Minus Aggressive (CMA) factor reflects differences in investment patterns, calculated using *Total Assets* to assess investment growth.

$$\text{CMA} = \frac{S/C + B/C}{2} - \frac{S/A + B/A}{2}$$

Where: S and B denote Small and Big firms, respectively. C and A correspond to Conservative and Aggressive investment patterns, respectively.

Table B2: Summary of Financial and Market Data Utilization

Data Variable	**Used For**
Closing Bid Price	Return on Assets, Momentum, Market Capitalization
Number of Shares Outstanding	Market Capitalization
Book Value per Share	Book Equity, Book-to-Market Ratio
Total Assets	Investment Factor
Operating Expenses	Operating Profitability
Net Revenues	Operating Profitability
OMX Stockholm All-Share Index	Market Return Proxy
One-Month Treasury Bill Rate	Risk-Free Rate

Portfolio Formation

At the end of each month, stocks are sorted into portfolios based on the collected financial and market data. Monthly value-weighted returns are calculated for each portfolio, where the weights are based on market capitalization at the end of the previous month. This approach follows standard practices in asset pricing literature (Campbell et al., 1997). The sorting criteria and corresponding data variables are as follows:

Size Portfolios: Stocks are divided into two groups based on Market Capitalization, also called Market Equity (ME), calculated as *Number of Shares Outstanding* × *Closing Bid Price*:

- *Small (S)*: Bottom 80% of ME.
- *Big (B)*: Top 20% of ME.

Value Portfolios: Within each size group, stocks are sorted into three B/M categories using *Book Value per Share* and *Closing Bid Price*:

- *Low B/M (Growth)*: Bottom 30%.
- *Neutral B/M*: Middle 40%.
- *High B/M (Value)*: Top 30%.

This results in six size-value portfolios: S/L, S/N, S/H, B/L, B/N, B/H.

Momentum Portfolios: Stocks are sorted within each size group based on past returns derived from *Closing Bid Price*:

- *Losers (Lo)*: Bottom 10%.
- *Winners (Wi)*: Top 10%.

This yields four momentum portfolios: S/Lo, S/Wi, B/Lo, B/Wi.

Profitability Portfolios: For the FF5 model, stocks are sorted within each size group based on Operating Profitability (OP), calculated using *Operating Expenses* and *Net Revenues*:

- *Weak (W)*: Bottom 30%.
- *Neutral (N)*: Middle 40%.
- *Robust (R)*: Top 30%.

This produces six profitability portfolios: S/W, S/N, S/R, B/W, B/N, B/R.

Investment Portfolios: Stocks are sorted within each size group based on Investment Growth (INV), derived from *Total Assets*:

- *Aggressive (A)*: Top 30%.
- *Neutral (N)*: Middle 40%.
- *Conservative (C)*: Bottom 30%.

This results in six investment portfolios: S/A, S/N, S/C, B/A, B/N, B/C.

Table B3: Interpretation of β Coefficients Across Asset Pricing Models

Model	Factor	Coefficient (β)	Interpretation
CAPM	Market ($r_{mt} - r_{ft}$)	β_i	Measures the asset's sensitivity to market movements. $\beta_i > 1$: higher volatility than the market; $\beta_i < 1$: lower volatility.
FF3	SMB (Small Minus Big)	β_{2i}	Exposure to size risk. Positive: tilt towards small-cap; Negative: tilt towards large-cap.
	HML (High Minus Low)	β_{3i}	Exposure to value risk. Positive: tilt towards value stocks; Negative: tilt towards growth stocks.
FF4	MOM (Momentum)	β_{4i}^{FF4}	Sensitivity to momentum factor. Positive: follows past winners; Negative: follows past losers.
FF5	RMW (Robust Minus Weak)	β_{4i}^{FF5}	Exposure to profitability risk. Positive: tilt towards profitable firms; Negative: tilt towards less profitable firms.
	CMA (Conservative Minus Aggressive)	β_{5i}^{FF5}	Exposure to investment risk. Positive: tilt towards conservative investment; Negative: tilt towards aggressive investment.

Table B4: VIF Values of the Factors in Fama-French Three factor Model (FF3)

Mkt-RF	SML_FF3_FF4	HML_FF3_FF4_FF5
1.053	1.020	1.035

Table B5: VIF Values of the Factors in Fama-French-Carhart Four Factor Model (FF4)

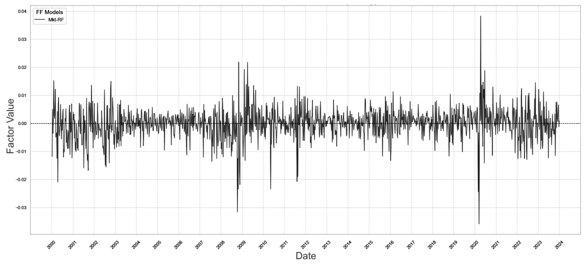
Mkt-RF	SML_FF3_FF4	HML_FF3_FF4_FF5	FF4_MOM
1.093	1.021	1.036	1.038

Table B6: VIF Values of the Factors in Fama-French Five factor Model (FF5)

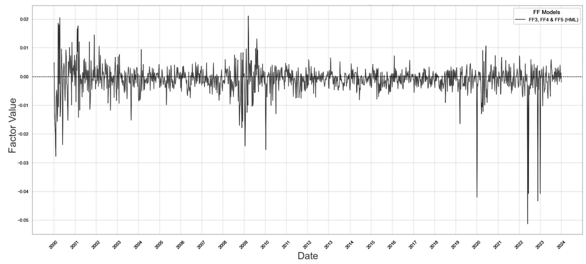
Mkt-RF	SML_FF5	HML_FF3_FF4_FF5	FF5_CMA	FF5_RMW
1.067	1.049	1.082	1.060	1.036

Note: All of the models' VIF assessments present values that are below the $>$ 5 threshold, suggesting minimal multicollinearity. This implies that the factors do not significantly affect one another's effects, confirming the stability and dependability of the regression's results and validating the model specifications used in the analysis (Gujarati, 2009, p. 340).

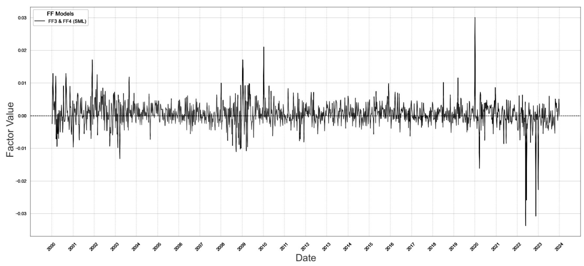
Figure B1: Weekly Variations of Fama-French Factors



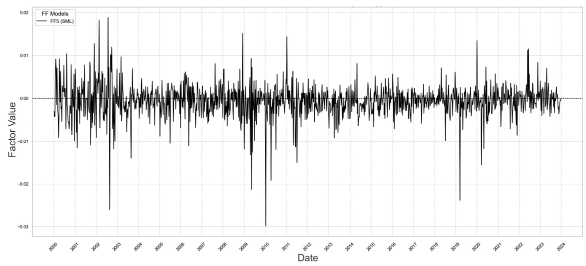
(a) Mkt-RF



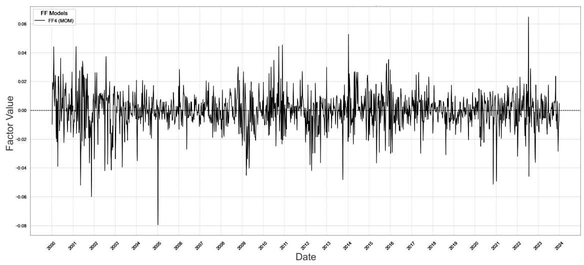
(b) HML



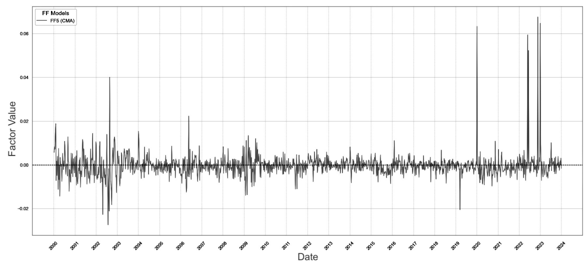
(c) SML (FF3 & FF4)



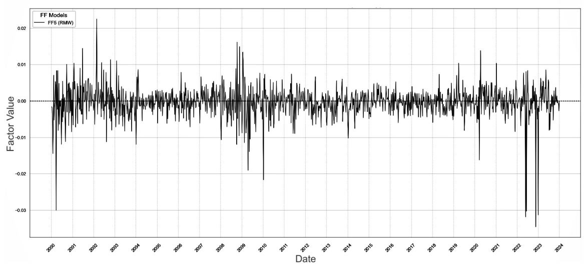
(d) SML (FF5)



(e) MOM (FF4)



(f) CMA (FF5)

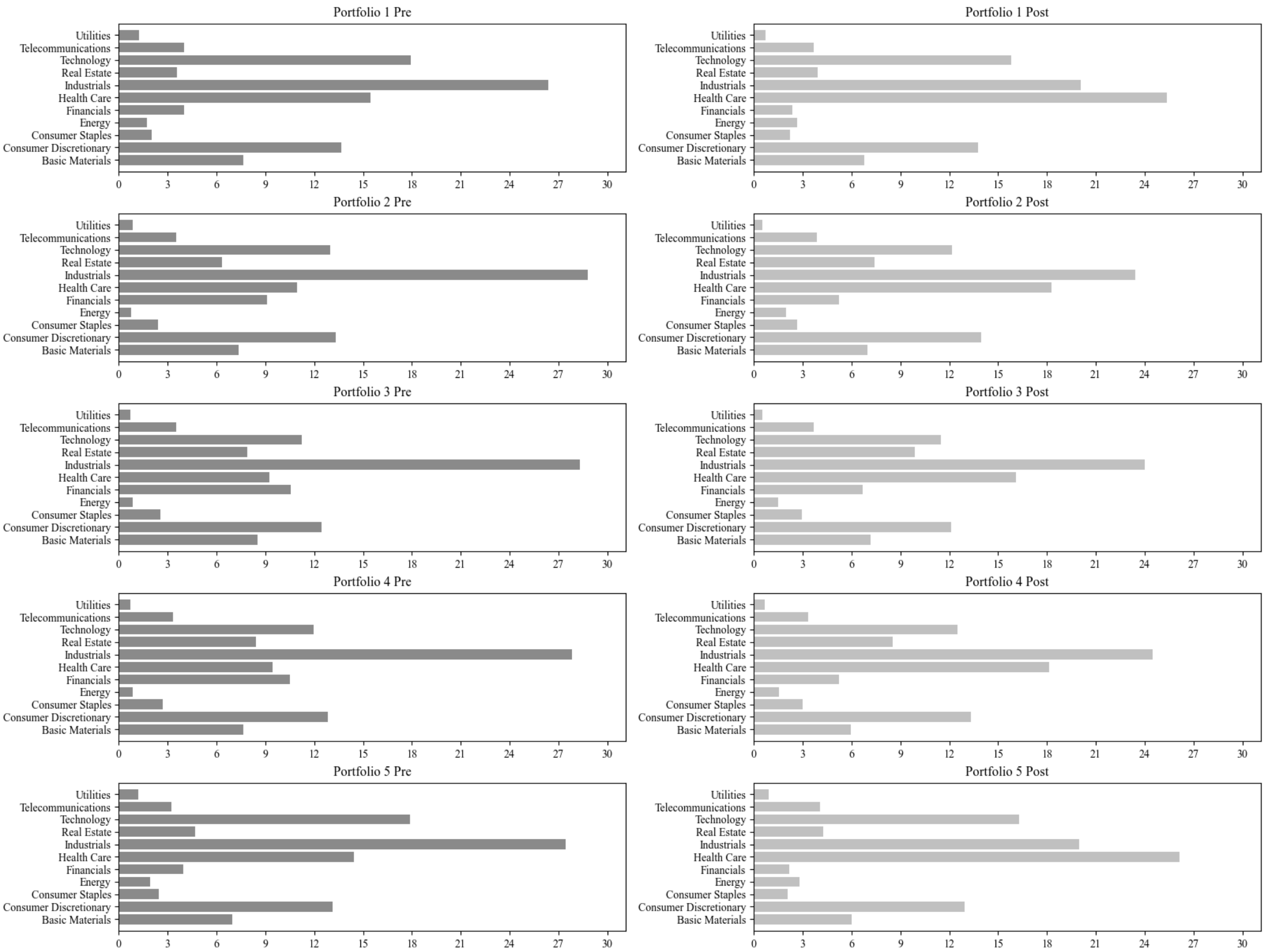


(g) RMW (FF5)

Note: This figure displays weekly aggregated variations of Fama-French factors from January 1st, 2000, to December 31st, 2024. The visualization of these factors highlights their fluctuations around a normalized mean, revealing any outliers or unusual patterns. This analysis is essential for validating the stability and consistency of these factors, which supports their reliability for inclusion in asset pricing models.

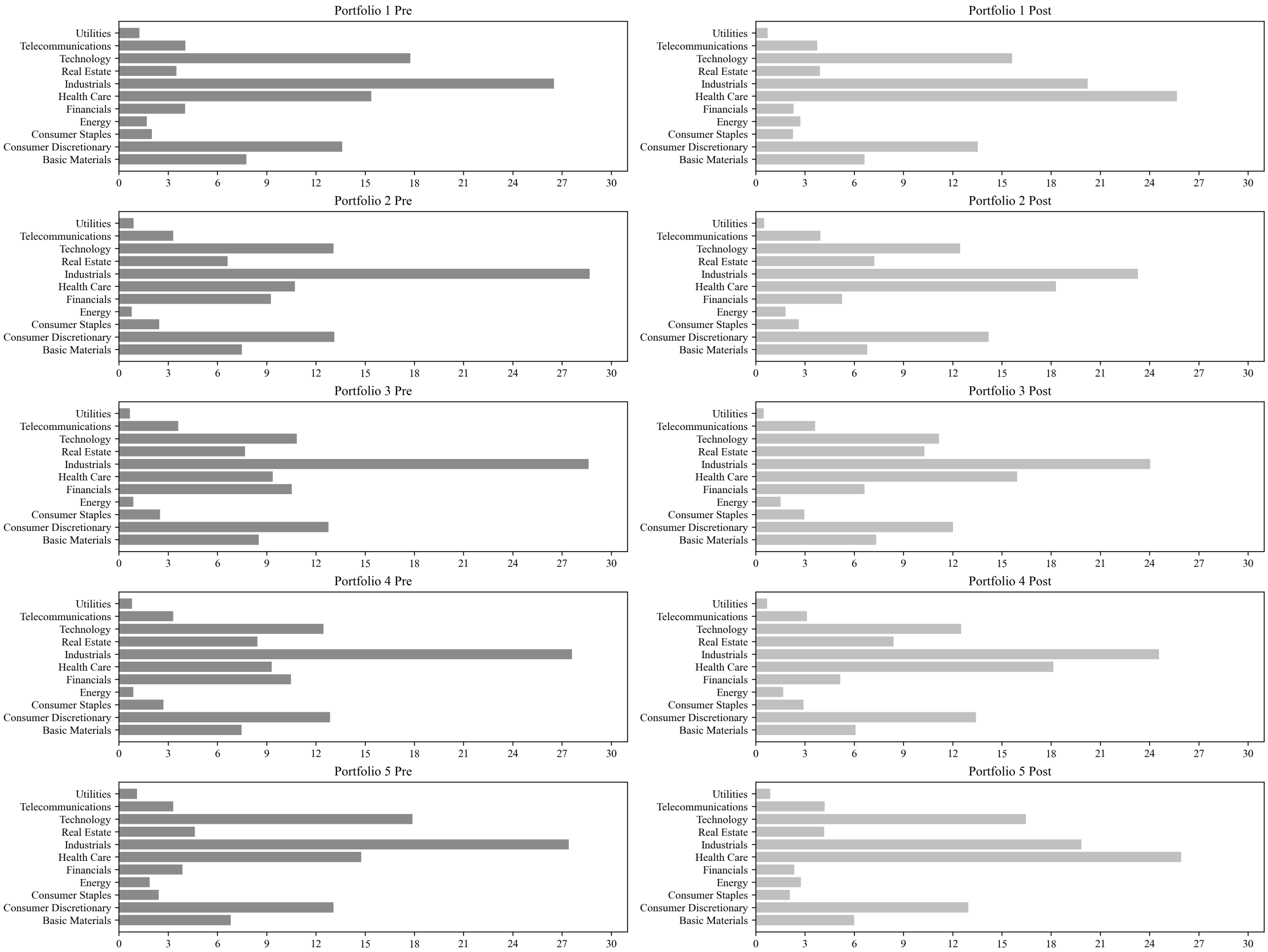
Appendix C: Regressions and Other Results

Figure C1: Industry distribution across portfolios (FF3 model) Pre and Post-Paris Agreement



Note: The left side represents the pre-Paris Agreement period, while the right side represents the post-Paris Agreement period. Portfolios are arranged from top to bottom in descending order of climate beta, with the lowest beta at the top and the highest beta at the bottom.

Figure C2: Industry distribution across portfolios (FF4 model) Pre and Post-Paris Agreement



Note: The left side represents the pre-Paris Agreement period, while the right side represents the post-Paris Agreement period. Portfolios are arranged from top to bottom in descending order of climate beta, with the lowest beta at the top and the highest beta at the bottom.

Topic 3 - Quantile Portfolio Sort - Full Period

Estimating Alpha for Topic 3 transition FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.955	R-squared:	0.001	
Observations:	287	F-statistic:	0.1088			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0012	0.001	-0.976	0.329	-0.004	0.001
Mkt-RF	0.0061	0.227	0.027	0.979	-0.438	0.451
FF3_SMB	-0.2767	0.821	-0.337	0.736	-1.885	1.332
FF3_HML	0.2166	0.660	0.328	0.743	-1.076	1.509
Skew:	1.712	Durbin-Watson:	1.965			

Estimating Alpha for Topic 3 transition FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0796	R-squared:	0.024	
Observations:	287	F-statistic:	2.111			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0024	0.001	-2.430	0.015	-0.004	-0.000
Mkt-RF	-0.1243	0.156	-0.797	0.425	-0.430	0.181
FF4_SMB	-0.1894	0.812	-0.233	0.816	-1.780	1.402
FF4_HML	-0.0680	0.521	-0.130	0.896	-1.090	0.954
FF4_MOM	-0.3811	0.133	-2.876	0.004	-0.641	-0.121
Skew:	0.296	Durbin-Watson:	2.059			

Estimating Alpha for Topic 3 transition FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.683	R-squared:	0.014	
Observations:	287	F-statistic:	0.6228			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0013	0.001	-1.260	0.208	-0.003	0.001
Mkt-RF	-0.1318	0.193	-0.683	0.494	-0.510	0.246
FF5_SMB	-0.3843	0.746	-0.515	0.607	-1.847	1.078
FF5_HML	0.0587	0.607	0.097	0.923	-1.130	1.248
FF5_RMW	-1.1039	0.771	-1.432	0.152	-2.615	0.407
FF5_CMA	0.0643	0.716	0.090	0.928	-1.338	1.467
Skew:	1.484	Durbin-Watson:	2.156			

Topic 12 - Quantile Portfolio Sort - Full Period

Estimating Alpha for Topic 12 transition FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.195	R-squared:	0.013	
Observations:	287	F-statistic:	1.576			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0034	0.001	-2.394	0.017	-0.006	-0.001
Mkt-RF	-0.2950	0.186	-1.584	0.113	-0.660	0.070
FF3_SMB	0.7367	0.881	0.836	0.403	-0.990	2.463
FF3_HML	0.1169	0.735	0.159	0.874	-1.324	1.558
Skew:	-2.834	Durbin-Watson:	1.896			

Estimating Alpha for Topic 12 transition FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.145	R-squared:	0.051	
Observations:	287	F-statistic:	1.722			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0036	0.001	-3.451	0.001	-0.006	-0.002
Mkt-RF	-0.2909	0.187	-1.557	0.120	-0.657	0.075
FF4_SMB	1.1652	0.778	1.498	0.134	-0.360	2.690
FF4_HML	0.4031	0.769	0.524	0.600	-1.105	1.911
FF4_MOM	0.4594	0.408	1.125	0.261	-0.341	1.260
Skew:	-2.219	Durbin-Watson:	1.961			

Estimating Alpha for Topic 12 transition FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.311	R-squared:	0.037	
Observations:	287	F-statistic:	1.197			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0026	0.001	-2.128	0.033	-0.005	-0.000
Mkt-RF	-0.2349	0.189	-1.245	0.213	-0.605	0.135
FF5_SMB	0.8160	0.686	1.190	0.234	-0.528	2.160
FF5_HML	0.3418	0.579	0.590	0.555	-0.794	1.477
FF5_RMW	-0.7845	0.823	-0.954	0.340	-2.397	0.828
FF5_CMA	-1.1172	1.075	-1.039	0.299	-3.225	0.990
Skew:	-0.092	Durbin-Watson:	1.850			

Topic 13 - Quantile Portfolio Sort - Full Period

Estimating Alpha for Topic 13 transition FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0298	R-squared:	0.035	
Observations:	287	F-statistic:	3.029			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0002	0.001	0.182	0.856	-0.002	0.002
Mkt-RF	0.2654	0.189	1.403	0.161	-0.105	0.636
FF3_SMB	-0.1752	0.509	-0.344	0.731	-1.174	0.823
FF3_HML	-1.3492	0.492	-2.741	0.006	-2.314	-0.384
Skew:	0.403	Durbin-Watson:	1.936			

Estimating Alpha for Topic 13 transition FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.143	R-squared:	0.045	
Observations:	287	F-statistic:	1.732			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0002	0.001	-0.129	0.898	-0.003	0.002
Mkt-RF	0.3191	0.204	1.562	0.118	-0.081	0.720
FF4_SMB	-0.0171	0.659	-0.026	0.979	-1.309	1.275
FF4_HML	-1.4450	0.651	-2.220	0.026	-2.721	-0.169
FF4_MOM	-0.3797	0.274	-1.385	0.166	-0.917	0.158
Skew:	-0.119	Durbin-Watson:	1.966			

Estimating Alpha for Topic 13 transition FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio spread return	Prob (F-statistic):	0.180	R-squared:	0.054	
Observations:	287	F-statistic:	1.533			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0010	0.002	0.612	0.541	-0.002	0.004
Mkt-RF	0.1837	0.184	1.001	0.317	-0.176	0.543
FF5_SMB	-0.7001	0.733	-0.955	0.340	-2.137	0.737
FF5_HML	-0.6650	0.458	-1.452	0.147	-1.563	0.233
FF5_RMW	-0.5835	0.774	-0.754	0.451	-2.100	0.933
FF5_CMA	1.4245	1.050	1.357	0.175	-0.633	3.482
Skew:	0.571	Durbin-Watson:	1.908			

Topic 16 - Quantile Portfolio Sort - Full Period

Estimating Alpha for Topic 16 (physical) FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.377	R-squared:	0.010	
Observations:	287	F-statistic:	1.035			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0009	0.001	0.823	0.411	-0.001	0.003
Mkt-RF	0.2266	0.147	1.540	0.124	-0.062	0.515
FF3_SMB	0.4770	0.611	0.780	0.435	-0.721	1.675
FF3_HML	-0.0323	0.446	-0.072	0.942	-0.906	0.841
Skew:	-0.190	Durbin-Watson:	1.694			

Estimating Alpha for Topic 16 (physical) FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.00663	R-squared:	0.038	
Observations:	287	F-statistic:	3.633			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0004	0.001	-0.405	0.686	-0.002	0.002
Mkt-RF	0.2316	0.160	1.451	0.147	-0.081	0.544
FF4_SMB	0.3303	0.664	0.497	0.619	-0.972	1.632
FF4_HML	-0.6912	0.429	-1.612	0.107	-1.532	0.149
FF4_MOM	-0.3983	0.131	-3.030	0.002	-0.656	-0.141
Skew:	-0.762	Durbin-Watson:	1.777			

Estimating Alpha for Topic 16 (physical) FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.460	R-squared:	0.017	
Observations:	287	F-statistic:	0.9333			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0017	0.001	1.415	0.157	-0.001	0.004
Mkt-RF	0.2433	0.156	1.564	0.118	-0.062	0.548
FF5_SMB	-0.0356	0.412	-0.086	0.931	-0.843	0.772
FF5_HML	-0.5674	0.366	-1.552	0.121	-1.284	0.149
FF5_RMW	0.0809	0.480	0.169	0.866	-0.860	1.021
FF5_CMA	0.1931	0.575	0.336	0.737	-0.933	1.320
Skew:	0.101	Durbin-Watson:	1.757			

Topic 3 - Decile Portfolio Sort - Full Period

Estimating Alpha for Topic 3 transition Full Period FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.324	R-squared:	0.007	
Observations:	287	F-statistic:	1.165			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0010	0.001	-0.677	0.498	-0.004	0.002
Mkt-RF	-0.1265	0.252	-0.502	0.616	-0.620	0.367
FF3_SMB	-0.4880	1.166	-0.418	0.676	-2.774	1.798
FF3_HML	-0.8465	0.541	-1.565	0.118	-1.907	0.214
Skew:	0.376	Durbin-Watson:	2.114			

Estimating Alpha for Topic 3 transition Full Period FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.525	R-squared:	0.008	
Observations:	287	F-statistic:	0.802			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0016	0.001	-1.198	0.231	-0.004	0.001
Mkt-RF	-0.0580	0.218	-0.266	0.790	-0.485	0.369
FF4_SMB	-0.6669	1.189	-0.561	0.575	-2.997	1.663
FF4_HML	-0.9027	0.561	-1.610	0.107	-2.002	0.196
FF4_MOM	0.0429	0.165	0.259	0.796	-0.282	0.367
Skew:	0.009	Durbin-Watson:	2.172			

Estimating Alpha for Topic 3 transition Full Period FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.105	R-squared:	0.021	
Observations:	287	F-statistic:	1.842			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0018	0.001	-1.269	0.204	-0.004	0.001
Mkt-RF	0.0579	0.247	0.234	0.815	-0.427	0.543
FF5_SMB	-0.6317	1.135	-0.557	0.578	-2.856	1.593
FF5_HML	-1.2951	0.554	-2.339	0.019	-2.380	-0.210
FF5_RMW	-1.3145	1.026	-1.281	0.200	-3.326	0.697
FF5_CMA	0.2548	0.651	0.391	0.695	-1.021	1.530
Skew:	0.336	Durbin-Watson:	2.055			

Topic 12 - Decile Portfolio Sort - Full Period

Estimating Alpha for Topic 12 transition Full Period FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.642	R-squared:	0.008	
Observations:	287	F-statistic:	0.559			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0029	0.002	-1.741	0.082	-0.006	0.000
Mkt-RF	0.0036	0.251	0.014	0.989	-0.488	0.495
FF3_SMB	0.6370	0.980	0.650	0.516	-1.283	2.557
FF3_HML	-0.8319	0.907	-0.918	0.359	-2.609	0.945
Skew:	-1.773	Durbin-Watson:	1.852			

Estimating Alpha for Topic 12 transition Full Period FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.416	R-squared:	0.016	
Observations:	287	F-statistic:	0.9854			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0026	0.001	-1.965	0.049	-0.005	-7.35e-06
Mkt-RF	-0.0578	0.249	-0.232	0.816	-0.546	0.431
FF4_SMB	1.1822	0.792	1.493	0.135	-0.370	2.734
FF4_HML	-0.3766	0.900	-0.419	0.676	-2.140	1.387
FF4_MOM	0.2575	0.297	0.868	0.386	-0.324	0.839
Skew:	-0.291	Durbin-Watson:	1.907			

Estimating Alpha for Topic 12 transition Full Period FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0825	R-squared:	0.021	
Observations:	287	F-statistic:	1.974			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0028	0.002	-1.581	0.114	-0.006	0.001
Mkt-RF	-0.1769	0.272	-0.651	0.515	-0.709	0.355
FF5_SMB	1.1273	0.857	1.316	0.188	-0.552	2.807
FF5_HML	-1.1522	0.785	-1.467	0.142	-2.691	0.387
FF5_RMW	0.5628	0.848	0.664	0.507	-1.099	2.225
FF5_CMA	0.2528	0.814	0.311	0.756	-1.342	1.848
Skew:	-0.648	Durbin-Watson:	1.897			

Topic 13 - Decile Portfolio Sort - Full Period

Estimating Alpha for Topic 13 transition Full Period FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.293	R-squared:	0.016	
Observations:	287	F-statistic:	1.247			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0014	0.002	0.851	0.395	-0.002	0.005
Mkt-RF	0.2192	0.289	0.759	0.448	-0.347	0.785
FF3_SMB	-0.7283	0.975	-0.747	0.455	-2.638	1.182
FF3_HML	-1.4329	0.850	-1.686	0.092	-3.099	0.233
Skew:	1.085	Durbin-Watson:	2.048			

Estimating Alpha for Topic 13 transition Full Period FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.623	R-squared:	0.022	
Observations:	287	F-statistic:	0.6563			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0016	0.002	0.992	0.321	-0.002	0.005
Mkt-RF	0.0383	0.258	0.149	0.882	-0.467	0.544
FF4_SMB	-1.4507	1.292	-1.123	0.261	-3.982	1.081
FF4_HML	-1.3300	0.925	-1.437	0.151	-3.144	0.484
FF4_MOM	-0.3778	0.485	-0.778	0.436	-1.329	0.574
Skew:	1.546	Durbin-Watson:	1.945			

Estimating Alpha for Topic 13 transition Full Period FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.421	R-squared:	0.014	
Observations:	287	F-statistic:	0.9955			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0028	0.002	1.579	0.114	-0.001	0.006
Mkt-RF	0.2055	0.263	0.782	0.434	-0.310	0.721
FF5_SMB	-1.0585	0.782	-1.353	0.176	-2.592	0.475
FF5_HML	-0.8781	0.655	-1.341	0.180	-2.161	0.405
FF5_RMW	-0.2524	1.002	-0.252	0.801	-2.216	1.712
FF5_CMA	0.4626	1.175	0.394	0.694	-1.840	2.766
Skew:	1.427	Durbin-Watson:	1.942			

Topic 16 - Decile Portfolio Sort - Full Period

Estimating Alpha for Topic 16 (physical) Full Period FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.179	R-squared:	0.016	
Observations:	287	F-statistic:	1.644			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0003	0.001	0.227	0.820	-0.003	0.003
Mkt-RF	0.3981	0.274	1.452	0.146	-0.139	0.935
FF3_SMB	-0.2927	0.775	-0.377	0.706	-1.812	1.227
FF3_HML	-0.9459	0.573	-1.651	0.099	-2.069	0.177
Skew:	-1.190	Durbin-Watson:	2.102			

Estimating Alpha for Topic 16 (physical) Full Period FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0554	R-squared:	0.031	
Observations:	287	F-statistic:	2.339			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0006	0.001	-0.398	0.691	-0.003	0.002
Mkt-RF	0.4022	0.254	1.584	0.113	-0.096	0.900
FF4_SMB	-0.2778	0.799	-0.348	0.728	-1.844	1.289
FF4_HML	-1.2196	0.564	-2.162	0.031	-2.325	-0.114
FF4_MOM	0.3180	0.202	1.575	0.115	-0.078	0.714
Skew:	-1.218	Durbin-Watson:	2.020			

Estimating Alpha for Topic 16 (physical) Full Period FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.00325	R-squared:	0.055	
Observations:	287	F-statistic:	3.649			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0011	0.002	-0.599	0.549	-0.005	0.002
Mkt-RF	0.2599	0.249	1.045	0.296	-0.228	0.747
FF5_SMB	0.1476	0.843	0.175	0.861	-1.505	1.800
FF5_HML	-1.4535	0.528	-2.751	0.006	-2.489	-0.418
FF5_RMW	1.0401	0.767	1.355	0.175	-0.464	2.544
FF5_CMA	-1.5628	0.563	-2.777	0.005	-2.666	-0.460
Skew:	-0.747	Durbin-Watson:	1.975			

Topic 3 - Quantile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.983	R-squared:	0.001	
Observations:	190	F-statistic:	0.05520			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0023	0.002	-1.319	0.187	-0.006	0.001
Mkt-RF	-0.1123	0.283	-0.396	0.692	-0.668	0.443
FF3_SMB	-0.1423	1.114	-0.128	0.898	-2.325	2.041
FF3_HML	0.0678	0.790	0.086	0.932	-1.480	1.616
Skew:	1.672	Durbin-Watson:	1.968			

Estimating Alpha for Topic 3 transition Post Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.390	R-squared:	0.031	
Observations:	97	F-statistic:	1.014			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	8.129e-06	0.002	0.005	0.996	-0.003	0.003
Mkt-RF	0.3859	0.273	1.414	0.157	-0.149	0.921
FF3_SMB	-1.0619	1.022	-1.039	0.299	-3.065	0.941
FF3_HML	1.0806	0.799	1.353	0.176	-0.485	2.646
Skew:	1.337	Durbin-Watson:	2.050			

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0206	R-squared:	0.038	
Observations:	190	F-statistic:	2.976			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0033	0.001	-2.240	0.025	-0.006	-0.000
Mkt-RF	-0.2508	0.186	-1.352	0.176	-0.614	0.113
FF4_SMB	-0.1105	1.119	-0.099	0.921	-2.304	2.083
FF4_HML	-0.2630	0.599	-0.439	0.661	-1.438	0.912
FF4_MOM	-0.4969	0.154	-3.229	0.001	-0.799	-0.195
Skew:	0.249	Durbin-Watson:	2.075			

Estimating Alpha for Topic 3 transition Post Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.268	R-squared:	0.028	
Observations:	97	F-statistic:	1.320			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0010	0.001	-1.004	0.316	-0.003	0.001
Mkt-RF	0.2584	0.253	1.021	0.307	-0.238	0.754
FF4_SMB	-0.7243	0.687	-1.055	0.292	-2.070	0.622
FF4_HML	1.0366	0.766	1.354	0.176	-0.464	2.537
FF4_MOM	0.0255	0.212	0.121	0.904	-0.390	0.441
Skew:	0.467	Durbin-Watson:	2.082			

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.970	R-squared:	0.009	
Observations:	190	F-statistic:	0.1792			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0009	0.002	-0.593	0.553	-0.004	0.002
Mkt-RF	-0.0846	0.260	-0.325	0.745	-0.594	0.425
FF5_SMB	-0.7537	0.969	-0.778	0.437	-2.654	1.146
FF5_HML	-0.3103	0.669	-0.464	0.643	-1.621	1.000
FF5_RMW	-0.6131	0.978	-0.627	0.531	-2.530	1.304
FF5_CMA	-0.2692	0.876	-0.307	0.759	-1.986	1.447
Skew:	1.537	Durbin-Watson:	2.171			

Estimating Alpha for Topic 3 transition Post Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.000298	R-squared:	0.153	
Observations:	97	F-statistic:	5.212			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0002	0.001	-0.146	0.884	-0.003	0.002
Mkt-RF	0.0119	0.283	0.042	0.966	-0.542	0.566
FF5_SMB	0.5625	0.812	0.693	0.488	-1.028	2.153
FF5_HML	0.4451	0.752	0.592	0.554	-1.030	1.920
FF5_RMW	-1.9900	0.639	-3.114	0.002	-3.243	-0.737
FF5_CMA	1.8366	0.810	2.267	0.023	0.249	3.424
Skew:	0.333	Durbin-Watson:	2.114			

Topic 12 - Quantile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.218	R-squared:	0.025	
Observations:	190	F-statistic:	1.492			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0051	0.003	-1.959	0.05	-0.011	-2.63e-05
Mkt-RF	-0.4694	0.319	-1.470	0.142	-1.095	0.156
FF3_SMB	1.2942	1.244	1.040	0.298	-1.145	3.733
FF3_HML	0.2836	0.893	0.318	0.751	-1.467	2.034
Skew:	-2.600	Durbin-Watson:	1.807			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.414	R-squared:	0.013	
Observations:	97	F-statistic:	0.9632			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0020	0.001	-2.611	0.009	-0.003	-0.000
Mkt-RF	-0.0957	0.204	-0.470	0.639	-0.495	0.304
FF3_SMB	-0.5652	0.655	-0.864	0.388	-1.848	0.718
FF3_HML	-0.2302	0.549	-0.420	0.675	-1.306	0.845
Skew:	-0.101	Durbin-Watson:	2.341			

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.204	R-squared:	0.076	
Observations:	190	F-statistic:	1.501			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0036	0.002	-2.177	0.029	-0.007	-0.000
Mkt-RF	-0.2803	0.292	-0.958	0.338	-0.854	0.293
FF4_SMB	1.5677	0.998	1.571	0.116	-0.388	3.524
FF4_HML	0.7839	0.961	0.816	0.415	-1.099	2.667
FF4_MOM	0.6157	0.485	1.271	0.204	-0.334	1.565
Skew:	-1.916	Durbin-Watson:	1.906			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0379	R-squared:	0.036	
Observations:	97	F-statistic:	2.655			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0049	0.001	-3.261	0.001	-0.008	-0.002
Mkt-RF	-0.2651	0.246	-1.079	0.281	-0.747	0.216
FF4_SMB	0.1187	0.958	0.124	0.901	-1.760	1.997
FF4_HML	-1.3426	0.596	-2.254	0.024	-2.510	-0.175
FF4_MOM	-0.2355	0.212	-1.109	0.268	-0.652	0.181
Skew:	-2.138	Durbin-Watson:	2.144			

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.185	R-squared:	0.065	
Observations:	190	F-statistic:	1.521			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0028	0.002	-1.605	0.109	-0.006	0.001
Mkt-RF	-0.1980	0.263	-0.753	0.452	-0.714	0.318
FF5_SMB	1.2598	0.976	1.290	0.197	-0.654	3.173
FF5_HML	0.3525	0.656	0.537	0.591	-0.934	1.639
FF5_RMW	-1.4643	0.996	-1.470	0.142	-3.417	0.488
FF5_CMA	-1.6200	1.171	-1.384	0.166	-3.915	0.675
Skew:	-0.067	Durbin-Watson:	1.786			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.292	R-squared:	0.051	
Observations:	97	F-statistic:	1.251			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0011	0.001	-1.022	0.307	-0.003	0.001
Mkt-RF	0.0687	0.206	0.334	0.738	-0.334	0.472
FF5_SMB	-0.2492	0.564	-0.442	0.659	-1.355	0.857
FF5_HML	0.4121	0.780	0.528	0.597	-1.117	1.941
FF5_RMW	1.0820	0.585	1.850	0.064	-0.064	2.229
FF5_CMA	0.7946	0.703	1.130	0.259	-0.584	2.173
Skew:	-0.305	Durbin-Watson:	1.846			

Topic 13 - Quantile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0385	R-squared:	0.056	
Observations:	190	F-statistic:	2.854			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0009	0.002	0.583	0.560	-0.002	0.004
Mkt-RF	0.3219	0.255	1.265	0.206	-0.177	0.821
FF3_SMB	-0.6161	0.588	-1.048	0.295	-1.769	0.536
FF3_HML	-1.6253	0.585	-2.777	0.005	-2.772	-0.478
Skew:	-0.235	Durbin-Watson:	1.907			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.541	R-squared:	0.013	
Observations:	97	F-statistic:	0.7232			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0002	0.002	0.103	0.918	-0.003	0.003
Mkt-RF	0.2524	0.324	0.778	0.437	-0.383	0.888
FF3_SMB	0.6975	1.127	0.619	0.536	-1.511	2.906
FF3_HML	-0.3574	0.782	-0.457	0.648	-1.889	1.175
Skew:	1.979	Durbin-Watson:	1.989			

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.105	R-squared:	0.078	
Observations:	190	F-statistic:	1.942			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0013	0.002	0.691	0.490	-0.002	0.005
Mkt-RF	0.4657	0.284	1.641	0.101	-0.090	1.022
FF4_SMB	-0.5108	0.813	-0.628	0.530	-2.104	1.083
FF4_HML	-1.7952	0.733	-2.450	0.014	-3.231	-0.359
FF4_MOM	-0.4900	0.310	-1.580	0.114	-1.098	0.118
Skew:	-0.677	Durbin-Watson:	1.948			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.576	R-squared:	0.019	
Observations:	97	F-statistic:	0.7264			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-4.298e-05	0.002	-0.024	0.981	-0.004	0.003
Mkt-RF	0.0981	0.302	0.325	0.745	-0.494	0.690
FF4_SMB	1.2413	1.125	1.103	0.270	-0.965	3.447
FF4_HML	0.0482	0.868	0.055	0.956	-1.653	1.750
FF4_MOM	0.2003	0.273	0.733	0.463	-0.335	0.736
Skew:	1.809	Durbin-Watson:	2.012			

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.225	R-squared:	0.076	
Observations:	190	F-statistic:	1.404			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0009	0.002	0.428	0.669	-0.003	0.005
Mkt-RF	0.1151	0.252	0.456	0.648	-0.379	0.609
FF5_SMB	-1.1229	0.997	-1.126	0.260	-3.077	0.831
FF5_HML	-0.6266	0.557	-1.124	0.261	-1.719	0.466
FF5_RMW	-0.6822	0.950	-0.718	0.473	-2.544	1.180
FF5_CMA	1.5913	1.205	1.321	0.187	-0.770	3.953
Skew:	-0.021	Durbin-Watson:	1.886			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.681	R-squared:	0.014	
Observations:	97	F-statistic:	0.6250			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0003	0.002	0.180	0.857	-0.003	0.004
Mkt-RF	0.1219	0.297	0.411	0.681	-0.460	0.704
FF5_SMB	0.5696	1.199	0.475	0.635	-1.781	2.920
FF5_HML	-0.9261	1.124	-0.824	0.410	-3.130	1.277
FF5_RMW	-0.3866	1.151	-0.336	0.737	-2.643	1.870
FF5_CMA	1.1536	1.051	1.098	0.272	-0.905	3.213
Skew:	2.308	Durbin-Watson:	1.977			

Topic 16 - Quantile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0200	R-squared:	0.038	
Observations:	190	F-statistic:	3.360			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0025	0.002	1.522	0.128	-0.001	0.006
Mkt-RF	0.4701	0.184	2.549	0.011	0.109	0.832
FF3_SMB	1.0654	0.708	1.504	0.133	-0.323	2.454
FF3_HML	0.2127	0.488	0.436	0.663	-0.743	1.169
Skew:	-0.079	Durbin-Watson:	1.616			

Estimating Alpha for Topic 16 (physical) Post Paris Agreement FF3 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0210	R-squared:	0.027	
Observations:	97	F-statistic:	3.401			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0002	0.001	-0.173	0.863	-0.003	0.003
Mkt-RF	-0.1852	0.355	-0.522	0.602	-0.881	0.510
FF3_SMB	-0.7235	1.150	-0.629	0.529	-2.978	1.531
FF3_HML	-0.9451	0.651	-1.451	0.147	-2.222	0.331
Skew:	-0.339	Durbin-Watson:	2.080			

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.00917	R-squared:	0.047	
Observations:	190	F-statistic:	3.475			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0006	0.001	0.395	0.693	-0.002	0.003
Mkt-RF	0.4068	0.188	2.163	0.031	0.038	0.775
FF4_SMB	0.7743	0.800	0.968	0.333	-0.794	2.343
FF4_HML	-0.5188	0.494	-1.050	0.294	-1.487	0.450
FF4_MOM	-0.3385	0.154	-2.202	0.028	-0.640	-0.037
Skew:	-0.726	Durbin-Watson:	1.737			

Estimating Alpha for Topic 16 (physical) Post Paris Agreement FF4 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.00261	R-squared:	0.061	
Observations:	97	F-statistic:	4.414			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0011	0.002	-0.718	0.473	-0.004	0.002
Mkt-RF	-0.0935	0.417	-0.224	0.823	-0.911	0.724
FF4_SMB	-0.6111	1.187	-0.515	0.607	-2.937	1.715
FF4_HML	-1.3437	0.601	-2.235	0.025	-2.522	-0.165
FF4_MOM	-0.6022	0.242	-2.487	0.013	-1.077	-0.128
Skew:	-0.416	Durbin-Watson:	1.979			

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.336	R-squared:	0.024	
Observations:	190	F-statistic:	1.150			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0031	0.002	1.921	0.055	-6.33e-05	0.006
Mkt-RF	0.4005	0.188	2.127	0.033	0.031	0.770
FF5_SMB	0.0374	0.473	0.079	0.937	-0.890	0.965
FF5_HML	-0.3679	0.387	-0.950	0.342	-1.127	0.391
FF5_RMW	0.1280	0.532	0.240	0.810	-0.915	1.171
FF5_CMA	0.0773	0.680	0.114	0.910	-1.256	1.410
Skew:	0.193	Durbin-Watson:	1.681			

Estimating Alpha for Topic 16 (physical) Post Paris Agreement FF5 model (Quintile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0747	R-squared:	0.036		
Observations:	97	F-statistic:	2.083				
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]	
Const	0.0003	0.002	0.136	0.891	-0.004	0.004	
Mkt-RF	0.0308	0.366	0.084	0.933	-0.686	0.748	
FF5_SMB	0.1525	1.121	0.136	0.892	-2.044	2.349	
FF5_HML	-1.9848	1.007	-1.970	0.049	-3.959	-0.010	
FF5_RMW	-0.1898	1.134	-0.167	0.867	-2.413	2.033	
FF5_CMA	0.9767	0.810	1.206	0.228	-0.610	2.564	
Skew:	-0.096	Durbin-Watson:	1.970				

Topic 3 - Decile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.447	R-squared:	0.006	
Observations:	190	F-statistic:	0.8899			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0004	0.002	-0.161	0.872	-0.005	0.004
Mkt-RF	-0.0624	0.340	-0.183	0.854	-0.729	0.604
FF3_SMB	-0.4356	1.616	-0.270	0.787	-3.602	2.731
FF3_HML	-0.9238	0.638	-1.447	0.148	-2.175	0.327
Skew:	0.237	Durbin-Watson:	2.085			

Estimating Alpha for Topic 3 transition Post Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.712	R-squared:	0.008	
Observations:	97	F-statistic:	0.4582			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0011	0.002	-0.624	0.532	-0.005	0.002
Mkt-RF	-0.0725	0.358	-0.202	0.840	-0.775	0.630
FF3_SMB	-0.8713	0.905	-0.963	0.335	-2.644	0.902
FF3_HML	-0.4690	0.965	-0.486	0.627	-2.360	1.422
Skew:	1.238	Durbin-Watson:	2.260			

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.317	R-squared:	0.012	
Observations:	190	F-statistic:	1.189			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0010	0.002	-0.443	0.658	-0.005	0.003
Mkt-RF	0.0628	0.275	0.228	0.819	-0.476	0.602
FF4_SMB	-0.5373	1.628	-0.330	0.741	-3.728	2.653
FF4_HML	-1.2714	0.623	-2.040	0.041	-2.493	-0.050
FF4_MOM	0.0160	0.191	0.084	0.933	-0.359	0.391
Skew:	-0.145	Durbin-Watson:	2.153			

Estimating Alpha for Topic 3 transition Post Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.511	R-squared:	0.023	
Observations:	97	F-statistic:	0.8283			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0004	0.002	-0.206	0.837	-0.004	0.003
Mkt-RF	-0.0720	0.404	-0.178	0.859	-0.864	0.720
FF4_SMB	-1.3945	1.140	-1.223	0.221	-3.629	0.840
FF4_HML	0.9664	1.055	0.916	0.360	-1.102	3.035
FF4_MOM	0.2420	0.286	0.845	0.398	-0.319	0.803
Skew:	1.051	Durbin-Watson:	2.332			

Estimating Alpha for Topic 3 transition Pre Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.152	R-squared:	0.025	
Observations:	190	F-statistic:	1.636			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0025	0.003	-0.933	0.351	-0.008	0.003
Mkt-RF	0.0608	0.385	0.158	0.875	-0.694	0.816
FF5_SMB	-0.6628	1.564	-0.424	0.672	-3.729	2.403
FF5_HML	-1.6047	0.616	-2.604	0.009	-2.813	-0.397
FF5_RMW	-1.1667	1.342	-0.870	0.384	-3.796	1.463
FF5_CMA	-0.2190	0.741	-0.296	0.767	-1.670	1.233

Estimating Alpha for Topic 3 transition Post Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.129	R-squared:	0.062	
Observations:	97	F-statistic:	1.758			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0009	0.002	0.410	0.682	-0.003	0.005
Mkt-RF	0.0528	0.398	0.133	0.894	-0.727	0.833
FF5_SMB	0.0508	0.940	0.054	0.957	-1.791	1.892
FF5_HML	-1.1425	1.063	-1.074	0.283	-3.227	0.942
FF5_RMW	-1.4905	1.214	-1.227	0.220	-3.871	0.890
FF5_CMA	2.9130	1.509	1.931	0.053	-0.044	5.870
Skew:	0.652	Durbin-Watson:	2.482			

Topic 12 - Decile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.427	R-squared:	0.018	
Observations:	190	F-statistic:	0.931			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0035	0.003	-1.216	0.224	-0.009	0.002
Mkt-RF	0.0008	0.346	0.002	0.998	-0.678	0.679
FF3_SMB	1.2630	1.413	0.894	0.372	-1.507	4.033
FF3_HML	-1.1538	1.123	-1.027	0.304	-3.355	1.048
Skew:	-1.684	Durbin-Watson:	1.830			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.377	R-squared:	0.044	
Observations:	97	F-statistic:	1.045			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0007	0.001	-0.535	0.593	-0.003	0.002
Mkt-RF	0.3781	0.356	1.062	0.288	-0.320	1.076
FF3_SMB	-1.7347	1.078	-1.609	0.108	-3.847	0.378
FF3_HML	1.1003	1.115	0.987	0.324	-1.085	3.286
Skew:	-0.128	Durbin-Watson:	2.027			

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.393	R-squared:	0.023	
Observations:	190	F-statistic:	1.030			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0031	0.002	-1.269	0.204	-0.008	0.002
Mkt-RF	-0.0366	0.356	-0.103	0.918	-0.735	0.661
FF4_SMB	1.7087	1.130	1.512	0.130	-0.506	3.923
FF4_HML	-0.5414	1.094	-0.495	0.621	-2.685	1.602
FF4_MOM	0.2557	0.362	0.706	0.480	-0.454	0.965
Skew:	-0.270	Durbin-Watson:	1.849			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.916	R-squared:	0.012	
Observations:	97	F-statistic:	0.239			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0010	0.001	-0.722	0.470	-0.004	0.002
Mkt-RF	-0.0066	0.308	-0.021	0.983	-0.611	0.598
FF4_SMB	-0.3958	0.973	-0.407	0.684	-2.302	1.510
FF4_HML	0.7173	1.112	0.645	0.519	-1.462	2.897
FF4_MOM	0.2674	0.317	0.845	0.398	-0.353	0.888
Skew:	0.386	Durbin-Watson:	2.055			

Estimating Alpha for Topic 12 transition Pre Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0697	R-squared:	0.031	
Observations:	190	F-statistic:	2.081			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0041	0.003	-1.437	0.151	-0.010	0.001
Mkt-RF	-0.3099	0.384	-0.808	0.419	-1.062	0.442
FF5_SMB	1.2459	1.209	1.030	0.303	-1.124	3.616
FF5_HML	-1.4887	0.903	-1.649	0.099	-3.258	0.281
FF5_RMW	0.3933	1.064	0.370	0.712	-1.691	2.478
FF5_CMA	0.0722	0.961	0.075	0.940	-1.811	1.955
Skew:	-0.661	Durbin-Watson:	1.861			

Estimating Alpha for Topic 12 transition Post Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.326	R-squared:	0.030	
Observations:	97	F-statistic:	1.179			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0003	0.002	-0.190	0.850	-0.004	0.003
Mkt-RF	0.3798	0.259	1.464	0.143	-0.129	0.888
FF5_SMB	0.0647	1.119	0.058	0.954	-2.129	2.259
FF5_HML	0.8921	1.047	0.852	0.394	-1.160	2.945
FF5_RMW	1.3823	0.805	1.718	0.086	-0.195	2.959
FF5_CMA	0.3307	0.759	0.436	0.663	-1.157	1.818
Skew:	-0.024	Durbin-Watson:	1.995			

Topic 13 - Decile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.295	R-squared:	0.025	
Observations:	190	F-statistic:	1.244			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0010	0.003	0.376	0.707	-0.004	0.006
Mkt-RF	0.1651	0.402	0.411	0.681	-0.622	0.952
FF3_SMB	-1.3600	1.218	-1.116	0.264	-3.748	1.028
FF3_HML	-1.8355	1.005	-1.826	0.068	-3.806	0.135
Skew:	0.863	Durbin-Watson:	2.007			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.864	R-squared:	0.006	
Observations:	97	F-statistic:	0.246			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0027	0.002	1.140	0.254	-0.002	0.007
Mkt-RF	0.1305	0.395	0.330	0.741	-0.644	0.905
FF3_SMB	0.8690	1.518	0.572	0.567	-2.107	3.845
FF3_HML	0.0553	1.148	0.048	0.962	-2.194	2.304
Skew:	2.120	Durbin-Watson:	2.161			

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.435	R-squared:	0.048	
Observations:	190	F-statistic:	0.953			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0028	0.003	1.026	0.305	-0.003	0.008
Mkt-RF	0.0749	0.378	0.198	0.843	-0.667	0.816
FF4_SMB	-2.4679	1.617	-1.526	0.127	-5.637	0.701
FF4_HML	-1.9118	1.082	-1.767	0.077	-4.033	0.209
FF4_MOM	-0.4710	0.568	-0.830	0.407	-1.584	0.642
Skew:	1.367	Durbin-Watson:	1.917			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.927	R-squared:	0.009	
Observations:	97	F-statistic:	0.219			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0019	0.002	0.789	0.430	-0.003	0.007
Mkt-RF	0.1950	0.478	0.408	0.683	-0.742	1.132
FF4_SMB	0.6340	1.694	0.374	0.708	-2.687	3.955
FF4_HML	0.9884	1.487	0.665	0.506	-1.926	3.903
FF4_MOM	0.1350	0.368	0.367	0.714	-0.586	0.856
Skew:	1.823	Durbin-Watson:	2.012			

Estimating Alpha for Topic 13 transition Pre Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.317	R-squared:	0.021	
Observations:	190	F-statistic:	1.187			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0039	0.002	1.594	0.111	-0.001	0.009
Mkt-RF	0.2662	0.357	0.746	0.456	-0.433	0.965
FF5_SMB	-1.6439	0.994	-1.653	0.098	-3.593	0.305
FF5_HML	-0.9651	0.739	-1.306	0.191	-2.413	0.483
FF5_RMW	0.0544	1.269	0.043	0.966	-2.434	2.542
FF5_CMA	0.5260	1.356	0.388	0.698	-2.132	3.184
Skew:	1.271	Durbin-Watson:	1.883			

Estimating Alpha for Topic 13 transition Post Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.824	R-squared:	0.008	
Observations:	97	F-statistic:	0.434			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0015	0.002	0.658	0.510	-0.003	0.006
Mkt-RF	0.1016	0.429	0.237	0.813	-0.740	0.943
FF5_SMB	0.4386	1.500	0.292	0.770	-2.501	3.378
FF5_HML	-1.0779	1.373	-0.785	0.432	-3.769	1.613
FF5_RMW	-0.8513	1.159	-0.734	0.463	-3.123	1.421
FF5_CMA	0.4388	1.442	0.304	0.761	-2.388	3.265
Skew:	1.923	Durbin-Watson:	2.137			

Topic 16 - Decile Portfolio Sort - Pre- Post Paris Agreement

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.306	R-squared:	0.014	
Observations:	190	F-statistic:	1.213			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0008	0.003	-0.307	0.759	-0.006	0.004
Mkt-RF	0.4091	0.390	1.048	0.295	-0.356	1.174
FF3_SMB	0.4199	0.970	0.433	0.665	-1.482	2.321
FF3_HML	-0.8268	0.698	-1.184	0.236	-2.195	0.541
Skew:	-1.077	Durbin-Watson:	2.074			

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF3 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.256	R-squared:	0.021	
Observations:	97	F-statistic:	1.374			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0020	0.002	1.215	0.224	-0.001	0.005
Mkt-RF	-0.0438	0.446	-0.098	0.922	-0.918	0.831
FF3_SMB	-1.4232	1.482	-0.960	0.337	-4.327	1.481
FF3_HML	-1.1243	0.732	-1.536	0.124	-2.559	0.310
Skew:	-1.323	Durbin-Watson:	2.304			

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.0427	R-squared:	0.045	
Observations:	190	F-statistic:	2.521			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0004	0.002	-0.181	0.856	-0.005	0.004
Mkt-RF	0.5737	0.348	1.648	0.099	-0.109	1.256
FF4_SMB	0.2978	0.921	0.323	0.747	-1.508	2.104
FF4_HML	-1.1114	0.636	-1.747	0.081	-2.359	0.136
FF4_MOM	0.4741	0.221	2.143	0.032	0.040	0.908
Skew:	-1.127	Kurtosis:	7.977	Durbin-Watson:	1.903	

Estimating Alpha for Topic 16 (physical) Post Paris Agreement FF4 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.418	R-squared:	0.030	
Observations:	97	F-statistic:	0.9885			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.00008	0.002	0.047	0.963	-0.003	0.004
Mkt-RF	-0.2552	0.482	-0.530	0.596	-1.200	0.689
FF4_SMB	-1.2095	1.570	-0.770	0.441	-4.287	1.868
FF4_HML	-1.5843	1.051	-1.508	0.132	-3.644	0.475
FF4_MOM	-0.2242	0.316	-0.709	0.478	-0.844	0.395
Skew:	-1.359	Kurtosis:	10.285	Durbin-Watson:	2.342	

Estimating Alpha for Topic 16 (physical) Pre Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.00144	R-squared:	0.078	
Observations:	190	F-statistic:	4.117			
Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	-0.0013	0.003	-0.445	0.656	-0.007	0.004
Mkt-RF	0.4301	0.361	1.193	0.233	-0.277	1.137
FF5_SMB	0.8237	1.008	0.817	0.414	-1.152	2.800
FF5_HML	-1.4460	0.640	-2.260	0.024	-2.700	-0.192
FF5_RMW	1.3657	0.813	1.679	0.093	-0.228	2.960
FF5_CMA	-1.9034	0.590	-3.228	0.001	-3.059	-0.748
Skew:	-0.770	Durbin-Watson:	1.885			

Estimating Alpha for Topic 16 (physical) Post Paris Agreement FF5 model (Decile Portfolios) - OLS

Dep. Variable:	Portfolio Spread Return	Prob (F-statistic):	0.328	R-squared:	0.038	
Observations:	97	F-statistic:	1.173			

Variable	Coef	Std Err	Z	P>|Z|	[0.025	0.975]
Const	0.0008	0.003	0.313	0.754	-0.004	0.006
Mkt-RF	-0.3967	0.501	-0.791	0.429	-1.379	0.586
FF5_SMB	-0.4236	1.489	-0.285	0.776	-3.341	2.494
FF5_HML	-2.3961	1.332	-1.799	0.072	-5.007	0.215
FF5_RMW	0.0273	1.854	0.015	0.988	-3.606	3.660
FF5_CMA	0.2712	1.216	0.223	0.823	-2.111	2.654

Skew:	-0.480	Durbin-Watson:	2.220