The Asset Pricing and Risk Management Implications of Climate Transition Risks

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Abstract

This thesis assesses the existence of a climate transition risk premium in U.S. equity and corporate bond markets. For this, I construct a novel index of climate transition risks using textual analysis and deep learning techniques. The findings of this thesis indicate a statistically significant climate transition risk premium. The existence of this risk premium is a more recent phenomenon since little evidence for this risk premium is found before 2012. Furthermore, to investigate how climate transition risks affect the return series of different industries, I use the quantile-on-quantile method by Sim and Zhou (2015). This approach reveals that climate transition risks not only have a negative impact on the return series of industries commonly believed to be at large risk due to a transition to a more sustainable economy, such as oil and petroleum industries, but also such risks negatively impact different manufacturing and consumer goods industries. Green assets, however, appear to react positively under such circumstances and can thus be seen by investors as vehicles to serve as safe havens against the financial impact of the climate transition.

Contents

1 Introduction

This thesis assesses the existence of a climate transition risk premium in U.S. equity and corporate bond markets. For this, I construct a novel index of climate transition risks using textual analysis and deep learning techniques inspired by the Economic Policy Uncertainty Index created by Baker, Bloom, and Davis (2016). This thesis provides evidence for a statistically significant climate transition risk premium in U.S. equity markets and long-term and short-term bond markets. The existence of this risk premium is a recent phenomenon, with no significant climate transition risk premium existing before 2012. Instead, most evidence for this risk premium stems from the period between 2012 and 2022. This climate transition risk premium is consistent with the general intertemporal hedging hypothesis by Merton (1973), which entails that investors are willing to accept reduced returns on assets that serve as effective hedges against risks associated with unfavorable changes in the investment opportunity set.

Furthermore, to deeper investigate how climate transition risks affect the return series of different industry portfolios, I make use of the quantile-on-quantile (QQ) approach developed by Sim and Zhou (2015). This approach reveals that not only industries that are most commonly associated with being at risk from the climate transition, such as the oil and petroleum sector, but also companies in the manufacturing and consumer goods industries see decreased returns in periods of increased climate transition risks. This finding has important risk management implications for the investment strategies of financial institutions such as banks and insurance companies. However, this thesis also finds evidence of green investment funds seeing increased returns in times of extreme climate transition risks, indicating a potential role fur such assets to serve as hedges or safe havens against climate transition risks.

As stated, this thesis uses textual analysis and deep learning techniques to create an index of climate transition risks. Using a Bidirectional Long Short-Term Memory (BiLSTM) neural network allows me to accurately label a large number of historical news articles from major media outlets as to whether or not they signal a tightening of climate policy. These articles are subsequently aggregated and used to generate the index used in this thesis. Furthermore, to discover the existence of climate risk premia, I make use of portfolio sorts. As shown by Bali, Engle, and Murray (2016) and Cattaneo, Crump, and Wang (2022), portfolio sorts can be seen as a two-step non-parametric estimator of the significance of asset-pricing factors that is able to discover potential non-linear relations between returns and asset-pricing factors. Additionally, to discover the nuances in the relationship between climate transition risks and the returns of various asset classes, I make use of the quantile-on-quantile (QQ) approach developed by Sim and Zhou (2015). This approach combines quantile regression and non-parametric estimation in the form of local linear regression.

I also find evidence for a negative contemporaneous correlation between changes in my climate transition index, excess stock and bond market returns, and the Industrial Production Index (IP), which measures macroeconomic activity. I also find some evidence that my climate transition index has predictive power of future excess stock and bond market returns. This finding further suggests that climate transition risks have asset pricing implications.

Previous investigations into the existence of climate-related risk premia in equity or bond markets in various economies have led to mixed findings. Similarly to me, Alessi, Ossola, and Panzica

(2019) and Bolton and Kacperczyk (2021) find evidence for a significant risk premium in E.U. and U.S. equity markets associated with firm-level CO2 emissions. Additionally, Faccini, Matin, and Skiadopoulos (2021) find evidence for a significant risk premium associated with climate transition risks in U.S. equity markets, Bansal, Kiku, and Ochoa (2016) find evidence for temperature risks carrying a sizable premium in U.S. equity markets, and Huynh and Xia (2021) report the existence of a negative risk premium associated with climate change news in general in U.S. corporate bond markets. However, in contrast to my findings for U.S. corporate bond markets, Bats, Bua, and Kapp (2023) did not find a significant risk premium associated with climate transition risks for the European Union, and Kennett, Diaz-Rainey, Biswas, and Kuruppuarachchi (2021) did not find a significant risk premium associated with climate transition risks in New Zealand equity markets in contrast to what I find for U.S. equity markets. Furthermore, the potential for green assets to serve as hedges or safe havens for climate transition risks that I find is in accordance with findings by authors such as Cepni, Demirer, and Rognone (2022).

In summary, I first construct a novel index of climate transition risks using textual analysis and deep learning techniques. Subsequently, I use this index to discover whether a climate transition risk premium in U.S. equity and both long-term and short-term bond markets exists by using portfolio sorts. This approach reveals that a climate transition risk premium has emerged only in recent years, with no significant climate transition risk premium existing before 2012. Instead, most evidence for this risk premium stems from the period between 2012 and 2022. I confirm the existence of a climate transition risk premium by additionally making use of the method by Bali and Engle (2010) using the Dynamic Conditional Correlation (DCC) model by Engle (2002) to seek whether the conditional covariation between assets and the climate transition factor induces a risk premium. As a final robustness check, I also follow Brogaard and Detzel (2015) by making use of factor-mimicking portfolios and Fama-MacBeth regressions. Additionally, I investigate how climate transition risks affect the return series of different industries using quantile-on-quantile regression. This method uncovers that the negative impact of the transition to a more sustainable economy is not limited to the return series of industries commonly believed to be at large risk due to a transition to a more sustainable economy but also various other industries. However, green assets appear to react positively under such circumstances and can thus be seen by investors as vehicles to serve as safe havens against the financial impact of the climate transition.

2 Background & Previous Research

This thesis comes in light of the growing interest in the effects of climate change on financial markets and the economy in general. Other authors have already extensively documented that climate change significantly impacts the economy. These include Dell, Jones, and Olken (2012), who find that increasing temperatures substantially reduce economic growth and growth rates while at the same time reducing agricultural output, industrial output, and political stability in less developed countries. Likewise, Burke, Hsiang, and Miguel (2015) find economic productivity to be a non-linear function in temperature for all countries and that unmitigated climate change can reshape the global economy, reducing global average incomes and increasing global income inequality. Also, authors such as Bansal et al. (2016) report that global warming significantly negatively affects asset valuations and that temperature risks carry a negative price. In addition, Bolton and Kacperczyk (2021) discover that companies with greater carbon emissions exhibit increased returns in the stock market, which cannot be attributed to existing risk factors. This suggests that investors may already be seeking compensation for the potential risks associated with exposure to carbon emissions.

Many authors have previously focused on the physical risks of climate change in the form of extreme climatic and weather events such as droughts, extreme heat, hurricanes, tornadoes, or wildfires. Such physical effects of climate change warrant the intervention of policymakers to counteract climate change. However, such interventions unavoidably lead to new policy-related climate transition risks, attracting various researchers' attention to this new avenue in which the climate can affect the economy. It is of the utmost importance for financial institutions such as banks or insurance companies to consider the consequences of such climate transition risks. These risks may manifest themselves in the form of liability risks, such as reputational damage, or in the form of regulatory risks, such as fines or sanctions by regulatory bodies. Furthermore, climate transition risks can also manifest themselves in the form of investment risks. Moving towards a more sustainable economy can lead to considerable shifts in firms' asset values that financial institutions may have on their balance sheet due to their exposure to climate transition-related risks. Such factors illustrate why financial institutions have a clear-cut incentive to consider climate transition risks in their business operations and investment strategies.

In recent years, various factors have led to increased pressure on policymakers to take action to address climate change. These include the near-unanimous consensus among climate scientists on human-caused global warming as illustrated by Cook, Oreskes, Doran, Anderegg, Verheggen, Maibach, Carlton, Lewandowsky, Skuce, Green et al. (2016) and IPCC (2013), and the growing increase in public awareness of environmental issues, with most Americans now thinking the government should be more proactive in counteracting climate change (Tyson, Kennedy, and Funk, 2021). Further contributing factors are the increasing prevalence of extreme weather events UNISDR et al. (2015) and factors such as the current ongoing global energy crisis.

However, despite this, climate transition risks have not led to a constant tightening of climate transition risks due to various factors. These include political factors due to some political leaders denying or underestimating the effects of climate change and economic factors such as placing more importance on short-term economic gains than long-term environmental goals. Additionally, factors such as lacking international coordination may prevent the implementation of further climate change-related legislation due to disagreements between countries over the distribution of costs and benefits concerning international cooperation to counteract climate change.

These developments raise the question of whether the effects of climate transition are priced in financial markets. The existence of such a climate transition risk premium has far-reaching consequences for financial institutions such as banks and insurance companies. If a substantial risk premium is present, it motivates institutions to create suitable risk management tools and strategies to obtain a desired level of exposure to the financial consequences of the climate transition. Furthermore, the existence of a climate transition risk premium may also prompt regulators such as the DNB or ECB to mandate further the incorporation of the effects of the transition to a more sustainable economy in stress tests and ORSAs. A timely discovery of the existence of a climate transition risk premium may thus enable financial institutions to both measure and price climate transition-related risks accurately, which makes it possible to adjust their risk appetites and build resilient portfolios while at the same time being better prepared for increased regulatory scrutiny.

This thesis sets out to combine and expand on several different strands of current economic literature. The first area that this thesis expands on is the creation of a novel index of climate transition risk via textual analysis. Some important works in economic and financial research that make use of such an approach are Engle, Giglio, Kelly, Lee, and Stroebel (2020), who have created an index that measures innovations in the news about climate risk, and Baker et al. (2016), who have created an index that measures economic policy uncertainty. Authors such as Gavriilidis (2021) and Basaglia, Carattini, Dechezleprêtre, and Kruse (2021) later extended upon the work of Baker et al. (2016) by creating indices of climate policy uncertainty. This thesis expands on the current literature by incorporating deep learning techniques to accurately distinguish between news articles that signal a further tightening of climate policy.

Secondly, this thesis investigates the existence of a climate transition risk premium in both U.S. equity and bond markets. Previously authors such as Alessi et al. (2019), Bolton and Kacperczyk (2021), Faccini et al. (2021), Bansal et al. (2016), Huynh and Xia (2021), Bats et al. (2023) and Kennett et al. (2021) find mixed evidence of the existence of climate change-related factors in equity and bond markets for various economies.

The third contribution is further investigating the potential of various asset classes to serve as a hedge or safe haven against climate transition risks. For this, I use the quantile-on-quantile (QQ) approach developed by Sim and Zhou (2015). The QQ approach combines quantile regression and non-parametric local linear regression. This approach makes it possible to unravel the nuances in the relationship between climate transition risks and the returns of various asset classes. Previously authors such as Ullah, Zhao, Amin, Syed, and Riaz (2023) and Zhu, Chen, Ren, Xing, and Hau (2022) have applied this approach to investigate the relationship between Economic Policy Uncertainty and stock market returns under different policy and stock market circumstances.

3 Construction of Climate Index

3.1 Background & Introduction

As stated, to investigate whether climate transition risks are priced in the cross-section of asset and bond returns and to investigate nuance features in the relationship between various asset returns and climate policy, it is first necessary to create an index that measures environmental policy pressure over time. To this end, I follow an approach similar to Baker et al. (2016) and Basaglia et al. (2021), who have constructed Economic Policy Uncertainty (EPU) and Climate Policy Uncertainty (CPU) indices.

The construction of the indices by Baker et al. (2016) and Basaglia et al. (2021) begins by searching ten of the largest U.S. newspapers for economic and policy uncertainty articles. These ten newspapers are USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the Wall Street Journal. Next, these articles are aggregated on a monthly and newspaper-wise basis and subsequently divided by the total number of articles in a newspaper during that same month to account for changes in the number of articles published in a given newspaper in that same period. Furthermore, Baker et al. (2016) normalize the resulting series to have a unit standard deviation for each newspaper. The final index is found by summing the resulting series for each newspaper to obtain a multi-newspaper index and re-normalizing this index to have an average value of 100 over the entire period.

This thesis deviates from the work of authors such as Basaglia et al. (2021) by, instead of focusing on environmental policy uncertainty, directly focusing on tightening climate transition policy. To this end, I use a Bidirectional Long-Short Term Memory (BiLSTM) neural network to label news articles to determine whether or not they indicate a tightening of climate policy. A BiLSTM is a type of recurrent neural network that has the ability to process sequential data in both forward and backward directions concurrently. This entails that the model can more accurately capture the context of a word in a sentence since the meaning of a word can be influenced by the surrounding words. Additionally, due to BiLSTM containing memory cells that have the ability to hold on to information for possibly long periods of time, BiLSTM can model long-term dependencies from the input sequence, which makes it a powerful tool for text classification purposes when the exact meaning of words may depend on other words that are far apart. Previously, authors such as Wang, Cai, Wang, Li, and Wang (2020), Deng, Cheng, and Wang (2021), and Trueman, Kumar, Narayanasamy, and Vidya (2021) have applied BiLSTM for news article classification.

3.2 Data Processing and BiLSTM Model Architecture & Construction

Concretely, the process of creating the index used in this thesis begins by collecting all news articles related to environmental protection published in "The New York Times", "USA Today", "The Wall Street Journal" and "The Washington Post" from January 1995 until December 2022 from the Factiva database. Subsequently, I read all 2338 articles stemming from "USA Today" and manually labeled them, corresponding to whether or not they indicate a further tightening in climate transition legislation. Finally, I use these articles to train a BiLSTM to label the articles from the other three newspapers.

The first step involved in this process is prepossessing the manually labeled articles. In this step, the news articles are stripped of stop words and punctuation, all characters are converted to lowercase, and the text is tokenized into individual words. Furthermore, lemmatization is applied to reduce the vocabulary size, reduce noise in the text data, and improve the generalization of the model. Lemmatizing words entails the reduction of inflected forms of a certain word to the base form. Next, with the tokenized words, a dictionary of unique words in the text data is created, and each word gets assigned a unique integer index. Next, to ensure that all input sequences are the same length, I pad the input sequences with zeros to make all sequences the same length as the largest input sequence. Finally, I randomly split the data into training and test sets.

The next step is to create word embeddings using a pre-trained GloVe embedding model developed by Pennington, Socher, and Manning (2014). The pre-trained word embeddings with GloVe (Global Vectors for Word Representation) are obtained by training on large corpora of text, such as Wikipedia, and are designed to capture the statistical properties of words by examining the co-occurrence statistics of words to capture the semantic and syntactic relationships between words. The central idea of GloVe is that words that frequently occur together should have similar embeddings, which is achieved by using a co-occurrence matrix that counts the number of times each word appears with every other word in the corpus. Next, a global word-word co-occurrence matrix that captures the overall distribution across the corpus is constructed using this co-occurrence matrix. Subsequently, this matrix is factorized to obtain word embeddings, and the resulting embedding can capture both global and local co-occurrence statistics of the words in the corpus.

Subsequently, it is now possible to build the BiLSTM model. After trial and error, I have decided to make use of a simple model architecture consisting of an embedding layer, a Bidirectional LSTM layer with dropout, a dense layer, and an output layer. This architecture is shown in Figure A1. This choice for a simpler architecture results from the simple model's relatively good performance, not warranting a more complex model that can lead to an unnecessary increase in training time and computational resources, a decrease in interpretability, and an increased chance of overfitting.

Each previously assigned word index is assigned to the corresponding word embedding in the embedding layer. Next, the Bidirectional LSTM layer processes the input sequences in both a forward and a backward direction. It combines the output of both directions to generate a sequence of hidden states. Here, additionally, dropout is applied to prevent overfitting. This entails that a random fraction of the neurons is set to 0 at each training step, reducing interdependencies and promoting the learning of more robust and generalized representations. This dropout effectively removes the contribution of those values to subsequent computations in the network, simulating the absence of that information and introducing a form of noise. Subsequently, the dense layer applies a linear transformation to the hidden states to create a sequence of output vectors. Finally, the output layer applies a sigmoid activation function to the output vectors to generate the final probability distribution over the two classes, indicating whether an article signals a tightening of climate policy.

The next step is compiling the model by specifying the loss function, optimizer, and evaluation metrics. In this case, I make use of binary cross-entropy as the loss function, Adam (Adaptive Moment Estimation) by Kingma and Ba (2017) as the optimization algorithm to update the weights of the BiLSTM and accuracy as the evaluation metric. The binary cross-entropy loss function measures how dissimilar the predicted and true probabilities of the target variable are. This loss function is given below in Equation (1).

$$L(y,\hat{y}) = \frac{1}{n}\sum_{i=1}^{N} -(y_i \cdot \log(\hat{y_i}) + (1-y_i)\cdot \log(1-\hat{y_i})) \tag{1}$$

In Equation (1), y is the true label equal to 0 or 1 depending on whether an article signals increased climate policy, and $\hat{y}$ is the predicted probability. This formula penalizes the model for making incorrect predictions with a high probability of the wrong class.

The Adam optimizer that is used can adapt the learning rate of each weight based on historical gradient information and simultaneously prevent the learning rate from quickly becoming too small by using an exponentially decaying average of past gradients. Furthermore, Adam uses a moving average of the past squared gradients to normalize gradient updates and prevent the optimization process from being dominated by a single feature. Empirical results by Kingma and Ba (2017) show that the Adam algorithm works well in practice.

With the model compiled, it is possible to train the model on the training data. For each epoch, the loss on the training data is computed using the binary cross-entropy loss function that measures the model's performance on the training data, and the model weights are updated accordingly. At the same time, the performance of this model is separately evaluated on the validation set. The updated weights are subsequently used as a basis for the next epoch. To prevent overfitting, this process continues for succeeding epochs until the evaluation loss stops decreasing for ten successive epochs. Finally, the weights of the best-performing model are stored. Figure A2 shows the loss for the training and test set over successive epochs, and Figure A3 shows the corresponding accuracy of the model on the training and test set.

3.3 Climate Index

Next, this best model is used to make predictions for the unlabeled news articles belonging to "The New York Times", "The Wall Street Journal", and "The Washington Post". Subsequently, the articles predicted to signal an increase in climate change legislation are aggregated based on the newspaper and the publication month and year. Following Baker et al. (2016), these articles are subsequently divided by the total number of articles published in that newspaper in that same period to account for changes in the number of articles published over time. Additionally, each newspaper's obtained series is normalized to have a unit standard deviation. Finally, these three indices are summed to obtain a multi-newspaper index. They are also subsequently re-normalized to have an average value of 100 over the entire period from 1995 to 2022. Figure 1 shows the resulting series.

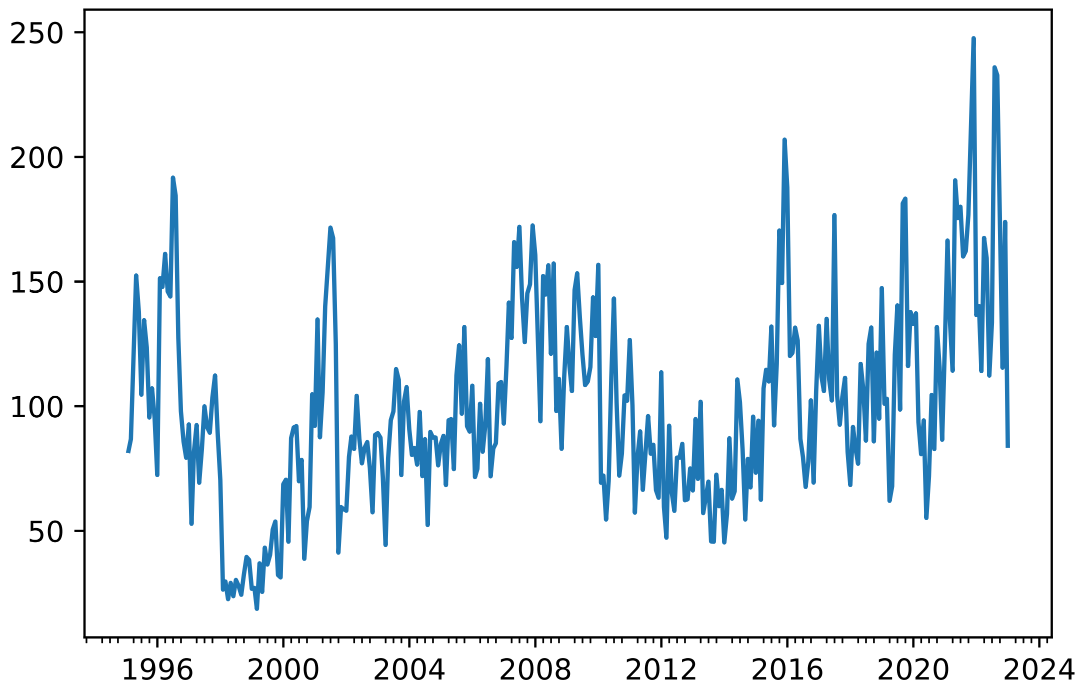


Figure 1: Climate Index

It is noticeable in Figure 1 that the climate transition index peaks as expected at several important events. The first such event occurred when the index peaked in the summer of 1996. The Second Conference of the Parties (COP-2) to the United Nations Framework Convention on Climate Change was held in Geneva during this period. Subsequently, in the late 1990s and early 2000s, the lack of interest in the effects of climate change led to reduced coverage related to climate legislation resulting in the index reaching its lowest recorded values.

Next, similar to what Gavriilidis (2021) finds for his index, my index records a peak in June of 2001 when President Bush released a statement on climate change. In the following years, the index remained relatively low until around 2006. During this period, several noticeable events occurred. First, in May 2006, "An Inconvenient Truth" was released, drawing attention to climate change's effects. Furthermore, in 2007, the Energy Independence and Security Act of 2007 was introduced in Congress and the Senate. This act aimed to promote energy efficiency, renewable energy development, and reduce dependence on foreign oil by establishing new standards for vehicle fuel economy and appliance efficiency, among other provisions.

The aftermath of the Global Financial Crisis may have caused a shift in public and media focus toward direct economic recovery and financial issues in the following years. As a result, climate change may have received less attention during this period as other concerns took priority. This is reflected in the climate index, shown in Figure 1, decreasing in the years after 2008. Furthermore, in November and December of 2015, the Paris Agreement was drafted that aimed to limit global warming. This resulted in a peak in the climate transition index.

Also, the index increased in the lead-up to the 2016 Presidential Election but seemed to decrease after Donald Trump's election, who pledged to reverse many existing instances of climate change legislation. However, during 2020 in the lead-up to the 2020 Presidential Election and the aftermath of Joe Biden's election, the index increased significantly. This signaled a shift towards a more proactive and ambitious approach to climate legislation in the United States, focusing on renewable energy, environmental justice, and international cooperation.

4 Asset Pricing Implications of Climate Policy

This section sets out to answer whether climate legislation proxied by the index of Figure 1 influences risk premia and whether or not it is priced in the cross-section of stock and corporate bond returns. Following Brogaard and Detzel (2015), I set out to answer this question by making use of the Intertemporal Capital Asset Pricing Model (ICAPM) by Merton (1973). As authors such as Brogaard and Detzel (2015) state, ICAPM suggests that expected excess returns should vary based on sensitivities to shocks in state variables that predict investment opportunities. If climate transition risks negatively impact investment opportunities, a negative relationship between an asset's excess return and its sensitivity to shocks in climate transition risk is expected.

I will start this section by introducing the ICAPM framework of Merton (1973). Subsequently, to examine the potential impact of climate transition risks on investment opportunities, following Brogaard and Detzel (2015), I investigate the relationship between changes in my Climate Transition Index and contemporaneous excess stock and bond market returns and macroeconomic activity. Subsequently, I continue by examining the forecasting power of my index for both macroeconomic activity and excess returns. This section concludes by directly investigating whether climate transition risks command a risk premium in stock and bond markets. I do this by making use of portfolio sorts. I confirm my results by investigating whether my results hold up when separately considering the different newspapers used in the construction of the Climate Transition Risk Index and by making use of the method by Bali and Engle (2010) using the Dynamic Conditional Correlation (DCC) model by Engle (2002) to seek whether the conditional covariation between assets and the climate transition factor induces a risk premium. As a final robustness check, I also follow Brogaard and Detzel (2015) by making use of factor-mimicking portfolios and Fama-MacBeth regressions.

4.1 ICAPM

The following overview of ICAPM is based on a lecture by Cochrane (2016) and on the book by Cochrane (2009). ICAPM is an extension of CAPM that is able to incorporate the stylized fact of the predictability of returns. When returns, r_t, are forecastable via a state variable for investment opportunities, x_t, it is implied in continuous time that returns follow the dynamics given in Equation (2), where Z_t is a Brownian motion.

$$dr_t = \mu(x_t)dt + \sigma(x_t)dZ_t \tag{2}$$

Under this framework, increases in x_t will increase returns, as positive changes in x_t signal increased investment opportunities. As Boons (2016) remarks, three of the most commonly used state variables affecting the investment opportunity set in the literature are dividend yields, the default spread, and the term spread. Consequently, given current wealth, increases in x_t will cause consumption c_t to increase, and marginal utility, $u'(c_t)$, will fall, provided that $u(c_t)$ is a monotonically increasing function, as is assumed here. Thus under ICAPM, news on state variables will affect marginal utility and, consequently, needs to be an additional factor.

Hence, the value function, which is the maximized value of some utility function, $V(W_t, x_t)$, will depend both on wealth and on the set of state variables x_t. The value function is given in Equation (3).

$$V(W_t, x_t) = max\ E_t \int_{s=0}^{\infty} e^{\delta s} u(c_{t+s}) ds\ s.t.\ W_t, x_t \tag{3}$$

Equation (3) states that an investor will seek to maximize utility, $u(c_t)$, given current wealth and investment opportunities. Furthermore, Equation (4) shows the wealth dynamics.

$$\begin{aligned} dW_t &= (W_t \cdot \mu(x_t) - c_t)dt + W_t \cdot \sigma(x_t) dZ_t \\ &= \mu_W(x_t)dt + \sigma_W(x_t)dZ_t \end{aligned} \tag{4}$$

Next, the discount factor Λ_t is defined in Equation (5).

$$\Lambda_t = g(f_t, t) = e^{-\delta t} u'(c_t) \tag{5}$$

Subsequently, it is possible to express marginal utility in Equation (5) in terms of factors that determine consumption, namely W_t and x_t, via the "envelope theorem" as is done in Equation (6).

$$\frac{\partial V(W_t, x_t)}{\partial W_t} = \frac{\partial u(c_t)}{\partial c_t} \tag{6}$$

This theorem states that at an optimum, the happiness obtained by saving and consuming a unit of currency should be equal. Subsequently, the discount factor can be written as in Equation (7).

$$\Lambda_t = e^{-\delta t} u'(c_t) = e^{-\delta t} V_W(W_t, x_t) \tag{7}$$

In Equation (7), V_W is the partial derivative of the value function with respect to wealth. Consequently, making use of Ito's lemma results in the expression given in Equation (8).

$$\begin{aligned} \frac{d\Lambda_t}{\Lambda_t} &= -\delta dt + \frac{W_t V_{WW}}{V_W} \frac{dW_t}{W_t} + \frac{V_{Wx}}{V_W} dx_t + 0.5 \cdot \frac{V_{WWW}}{V_W} d[W]_t \\ &+ 0.5 \cdot \frac{V_{Wxx}}{V_W} d[x]_t + \frac{V_{WWx}}{V_W} d[x, W]_t \\ &= -\delta dt + \frac{W_t V_{WW}}{V_W} \frac{dW_t}{W_t} + \frac{V_{Wx}}{V_W} dx_t \\ &+ 0.5 \cdot (\frac{V_{Wxx} \cdot \sigma^2}{V_W} + \frac{V_{WWW} \cdot \sigma_W^2}{V_W})dt + \frac{V_{WWx} \cdot \sigma_W \cdot \sigma}{V_W} dt \end{aligned} \tag{8}$$

Here, the second derivative terms are not fully worked out, considering that they will cancel out in the pricing equation given in Equation (9) due to them being dt terms and thus appearing in r_t^f.

$$
\begin{aligned}
E_t(dr_t^i) - r_t^f dt &= -E_t(\frac{d\Lambda_t}{\Lambda_t} dr_t^i) \\
&= (-\frac{W_t V_{WW}}{V_W}) E_t(\frac{dW_t}{W_t} dr_t^i) + (-\frac{V_{Wx}}{V_W}) E_t(dx_t dr_t^i) \\
&= A\ E_t(\frac{dW_t}{W_t} dr_t^i) + B\ E_t(dx_t dr_t^i)
\end{aligned} \tag{9}
$$

Here $A = (-\frac{W_t V_{WW}}{V_W})$ is the elasticity of marginal value with respect to wealth and can be referred to as the coefficient of relative risk aversion. $B = (-\frac{V_{Wx}}{V_W})$ is a coefficient reflecting state variable aversion. Since, in the remainder of this thesis, I work in discrete time due to the discrete nature of the Climate Transition Index, which is only updated monthly, it is convenient to discretize Equation (9). This discretization, which Cochrane (2009) notes is common in empirical work, is carried out in Equation (10).

$$
E_t(r_{t+1}^i - r_t^f) = A\ Cov_t(r_{t+1}^i, \Delta W_{t+1}) + B\ Cov_t(r_{t+1}^i, \Delta x_{t+1}), \tag{10}
$$

Furthermore, this can be reformulated as in Equation (11).

$$
E_t(r_{t+1}^i - r_t^f) = A\ Cov_t(r_{t+1}^i, r_{t+1}^m) + B\ Cov_t(r_{t+1}^i, \Delta x_{t+1}) \tag{11}
$$

Equation (11) states that investors receive higher expected returns as a reward, both for taking on systematic market risks and for taking on risks that are associated with unfavorable changes in the investment opportunity set. Consequently, as Brogaard and Detzel (2015) state, investors exhibit greater demand for assets that act as hedges against adverse shifts in the probabilities of future returns on the market portfolio. This increased demand drives up the prices of these assets and subsequently lowers their expected returns. Furthermore, as Cochrane (2009) states, Equation (9) leads to multiple linear discount factor models, as shown in Equation (12) and Equation (13).

$$
m_t = a + b' f_t \tag{12}
$$

$$
E(m_t r_t^e) = 0 \tag{13}
$$

As Cochrane (2009) states, the factors, f_t, are state variables for an investor's consumption portfolio decision. These factors thus include current wealth and other state variables that capture the conditional distribution of future asset returns or changes in the investment opportunity set.

4.2 The Relation Between Climate Transition Risks, Excess Returns & Macroeconomic Activity

Next, I investigate whether climate transition risks are an additional state variable that captures changes in the investment opportunity of future asset returns or changes in the investment opportunity set. As Cochrane (2009) notes, many authors commonly misuse the ICAPM framework as a "fishing license" to justify possible factors. One of the potential ways that Cochrane (2009) proposes to safeguard from this issue is to investigate whether investment-opportunity-set state variables have the ability to forecast returns or macroeconomic activity. To this end, I will explore the relation between my measure of climate transition risks and both contemporaneous and future returns and macroeconomic activity. Here, I make use of excess returns of the $S\&P$ 500 Index and $S\&P$ 500 Bond Index for return series, and following Boons (2016), I make use of the Chicago Fed National Activity Index (CFNAI) and Industrial Production Index (IP) as measures of macroeconomic activity.

The CFNAI aligns with the economic activity index formulated by Stock and Watson (1999). As stated by the Federal Reserve Bank of Chicago (2023), this index is a weighted average of 85 previously existing monthly economic activity indicators stemming from four broad categories: production and income, employment, personal consumption and housing, and sales, orders, and inventories. The CFNAI is constructed to have an average value of 0 and a standard deviation of 1. Positive values of this index correspond to economic activity growth above the trend, and negative values correspond to growth below the trend growth. Figure A4 shows the CFNAI between 1995 and 2022.

The Industrial Production Index is a monthly index published by the U.S. Federal Reserve Board. This index measures levels of real output in the manufacturing, mining, electric, and gas industries. The Federal Reserve Board (2023) indicates that as these sectors substantially influence the fluctuations in national output throughout the business cycle, the Industrial Production Index effectively captures significant structural developments within the economy. Figure A5 shows the Industrial Production Index between 1995 and 2022.

4.2.1 Relation with Contemporaneous Excess Returns & Macroeconomic Activity

I begin by investigating the relationship between climate transition risks and contemporaneous excess returns. Following Brogaard and Detzel (2015), I make use of the expression shown in Equation (14).

$$y_t = \alpha + \beta \cdot \Delta CTI_t + \gamma' \cdot \Delta X_t + \epsilon_t \tag{14}$$

In Equation (14), y_t refers to either log excess return of the S&P 500 Index or S&P 500 Bond Index or indices of macroeconomic activity. In addition, ΔCTI_t indicates changes in the Climate Transition Index. Furthermore, ΔX_t denotes changes in several standard economic state variables previously used by Brogaard and Detzel (2015). These are the VXO, the term spread, the default spread, RREL, and $\log(D/P)$. VXO is the implied volatility series on the S&P 100 index measuring economic uncertainty. Furthermore, the term spread is the spread between 3-month and 10-year Treasury bonds, and the default spread is the spread between AAA and BAA corporate bonds. Finally, RREL is the three-year U.S. Treasury Bill yield minus its twelve-month rolling average, and $\log(D/P)$ is the smoothed log dividend-price ratio on the S&P 500 Index, where D represents the 12-month rolling sum of dividends.

4.2.1.1 Stock Returns

Tables 1, 2, and 3 show the coefficients corresponding to the different state variables from Equation (14) when excess stock market returns are used as the dependent variable, both for the entire period considered between 1995 and 2022 and for the sub-periods between 1995 and 2012, and between 2012 and 2022. The corresponding heteroskedasticity- and autocorrelation-consistent Newey, West et al. (1987) standard error p-values are reported in brackets.

Control	(1)	(2)
$\Delta ClimateIndex$	-0.006 (0.016)	-0.005 (0.043)
ΔVXO	-0.031 (0.000)	
$\Delta Term$	-0.002 (0.853)	
$\Delta Default$	-0.010 (0.199)	
$\Delta RREL$	0.006 (0.653)	
$\Delta \log(D/P)$	0.005 (0.706)	

Table 1: Parameter Estimates Contemporaneous Stock Returns 1995-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-0.001 (0.732)	-0.003 (0.445)
ΔVXO	-0.036 (0.000)	
$\Delta Term$	-0.007 (0.589)	
$\Delta Default$	-0.004 (0.628)	
$\Delta RREL$	0.001 (0.966)	
$\Delta \log(D/P)$	0.000 (0.995)	

Table 2: Parameter Estimates Contemporaneous Stock Returns 1995-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-0.011 (0.002)	-0.007 (0.020)
ΔVXO	-0.029 (0.001)	
$\Delta Term$	0.015 (0.454)	
$\Delta Default$	-0.028 (0.018)	
$\Delta RREL$	0.023 (0.119)	
$\Delta \log(D/P)$	0.026 (0.254)	

Table 3: Parameter Estimates Contemporaneous Stock Returns 2012-2022

As seen in Table 1, when considering the entire period between 1995 and 2022, changes in the climate index are at a 5% significance level correlated with decreases in excess returns. This is the case, irrespective of controlling for different state variables. However, when examining Tables 2 and 3, it becomes apparent that this relation depends on the inclusion of more recent years since Table 2 shows that this relation between changes in the climate index and contemporaneous excess stock returns is not significant for the subperiod between 1995 and 2012.

4.2.1.2 Bond Returns

Next, Tables 4, 5, and 6 show the coefficients corresponding to the different state variables from Equation (14) when excess bond returns are used as the dependent variable, both for the entire period considered between 2003 and 2022 and for the sub-periods between 2003 and 2012, and between 2012 and 2022. Due to limited data availability, with only data from the $S\&P500$ Bond Index starting from 2003 being available to me, only data from 2003 until 2022 can be used in this section.

Control	(1)	(2)
$\Delta ClimateIndex$	0.001 (0.637)	0.005 (0.430)
ΔVXO	-0.003 (0.028)	
$\Delta Term$	-0.021 (0.001)	
$\Delta Default$	-0.001 (0.821)	
$\Delta RREL$	-0.006 (0.514)	
$\Delta \log(D/P)$	-0.006 (0.324)	

Table 4: Parameter Estimates Contemporaneous Bond Returns 2003-2022

Control	(1)	(2)
$\Delta ClimateIndex$	0.003 (0.231)	0.003 (0.261)
ΔVXO	-0.005 (0.243)	
$\Delta Term$	-0.021 (0.020)	
$\Delta Default$	0.001 (0.836)	
$\Delta RREL$	0.001 (0.962)	
$\Delta \log(D/P)$	-0.002 (0.805)	

Table 5: Parameter Estimates Contemporaneous Bond Returns 2003-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-0.003 (0.077)	-0.003 (0.096)
ΔVXO	-0.004 (0.014)	
$\Delta Term$	-0.021 (0.029)	
$\Delta Default$	-0.004 (0.416)	
$\Delta RREL$	-0.017 (0.118)	
$\Delta \log(D/P)$	-0.012 (0.214)	

Table 6: Parameter Estimates Contemporaneous Bond Returns 2012-2022

As seen from Table 4, contrasting to the findings from excess stock market returns, changes in the climate index are not significantly correlated with contemporaneous excess bond returns, both when controlling for state variables and when not. When examining Tables 5 and 6, it is noticeable that this is caused by the first sub-period between 2003 and 2012, as shown by Table 5. However, if only the later sub-period between 2012 and 2022 is considered, it can be seen that changes in the Climate Transition Risk Index are again negatively correlated with excess bond returns, albeit only at a 10% significance level.

4.2.1.3 Macroeconomic Activity

Tables 7, 8, and 9 show the coefficients corresponding to the different state variables from Equation (14) when the Chicago Fed National Activity Index is used as the dependent variable. Likewise, Tables 10, 11, and 12 show the coefficients when the Industrial Production Index is used as the dependent variable. Again, I conduct this analysis for the entire period and the two different sub-periods.

Control	(1)	(2)
$\Delta ClimateIndex$	-0.012 (0.706)	-0.037 (0.159)
ΔVXO	-0.060(0.408)	
$\Delta Term$	0.125 (0.151)	
$\Delta Default$	-0.304 (0.000)	
$\Delta RREL$	0.152 (0.083)	
$\Delta \log(D/P)$	-0.091 (0.000)	

Table 7: Parameter Estimates Contemporaneous CFNAI 1995-2022

Control	(1)	(2)
$\Delta ClimateIndex$	-0.020 (0.895)	-0.009 (0.832)
ΔVXO	-0.218 (0.284)	
$\Delta Term$	-0.058 (0.773)	
$\Delta Default$	-0.666 (0.136)	
$\Delta RREL$	0.150 (0.590)	
$\Delta \log(D/P)$	-0.281 (0.182)	

Table 8: Parameter Estimates Contemporaneous CFNAI 1995-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-0.032 (0.326)	-0.061 (0.059)
ΔVXO	-0.012 (0.739)	
$\Delta Term$	0.108 (0.001)	
$\Delta Default$	-0.265 (0.000)	
$\Delta RREL$	0.162 (0.000)	
$\Delta \log(D/P)$	-0.073 (0.000)	

Table 9: Parameter Estimates Contemporaneous CFNAI 2012-2022

Tables 7, 8, and 9 show that changes in my measure of climate transition risks do not seem to be significantly correlated with changes in the CFNAI. Only when considering the sub-period between 2012 and 2022 there appears to be a significant negative correlation at a 10% significance level. However, this significance disappears when controlling for the other economic state variables.

Control	(1)	(2)
$\Delta ClimateIndex$	-3.169 (0.000)	-32.589 (0.000)
ΔVXO	-3.115 (0.005)	
$\Delta Term$	1.534 (0.131)	
$\Delta Default$	8.345 (0.000)	
$\Delta RREL$	2.112 (0.039)	
$\Delta \log(D/P)$	-9.51 (0.000)	

Table 10: Parameter Estimates Contemporaneous Industrial Production Index 1995-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-2.062 (0.110)	-31.128 (0.000)
ΔVXO	-3.332 (0.011)	
$\Delta Term$	1.958 (0.093)	
$\Delta Default$	9.052 (0.000)	
$\Delta RREL$	0.686 (0.528)	
$\Delta \log(D/P)$	-12.19 (0.000)	

Table 11: Parameter Estimates Contemporaneous Industrial Production Index 1995-2012

Control	(1)	(2)
$\Delta ClimateIndex$	-4.067 (0.000)	-33.826 (0.000)
ΔVXO	-1.113 (0.311)	
$\Delta Term$	1.016 (0.266)	
$\Delta Default$	7.349 (0.000)	
$\Delta RREL$	2.700 (0.032)	
$\Delta \log(D/P)$	-8.526 (0.000)	

Table 12: Parameter Estimates Contemporaneous Industrial Production Index 2012-2022

Finally, Table 10 shows that changes in my measure of climate transition have, over the entire time period, a significant negative correlation with the Industrial Production Index. This is again largely driven by the last sub-period between 2012 and 2022, considering that Table 11 shows that the coefficient corresponding to changes in the climate index just falls short of being significant at the 10% significance level between 1995 and 2012. Meanwhile, Table 12 shows again that for the period between 2012 and 2022, the coefficient for changes in climate transition risks is highly significant. This indicates that changes in the climate transition index are contemporaneously correlated with a measure of macroeconomic activity, suggesting that climate transition risks affect investment opportunities.

4.2.2 Log Dividend Growth

Next, following Brogaard and Detzel (2015), I will test whether changes in my measure of climate transition risks affect future dividend growth. Previously, I have found that changes in my index are associated with decreases in current stock and bond market returns. Basic financial theory states that as asset prices can be seen as discounted expected future cash flows, this price drop can be explained by either negative changes in expected future cash flows or changes in discount rates. Previously, authors such as Lee, Wang, and Thinh (2023) and Heo (2021) have documented that exposure to climate-related risks can affect future cash flows. Similarly to Brogaard and Detzel (2015), I will test whether changes in my index of climate transition risks impact future dividend growth and, thus, cash flows. To investigate this, I make use of Equation (15).

$$\Delta d_{t,t+h} = \alpha + \beta \cdot \Delta CTI_t + \gamma' \cdot X_t + \epsilon_{t,t+h} \quad (15)$$

In Equation (15) $\Delta d_{t,t+h}$ stand for log dividend growth over months t to $t+h-1$. Δd_t is calculated as $\log(D_t) - \log(D_{t-1})$ and $\Delta d_{t,t+h} = \sum_{i=1}^{h} \Delta d_{t+i-1}$. Furthermore, Tables 13, 14, and 15 show the results from running the regression of Equation (15) while using VXO, the term spread, the default spread, and RREL as additional controls both for the entire period and for sub-periods.

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.001 (0.244)	0.001 (0.307)	0.002 (0.415)	0.003 (0.462)
VXO	-0.005 (0.035)	-0.017 (0.018)	-0.030 (0.030)	-0.045 (0.118)
TERM	0.004 (0.212)	0.013 (0.119)	0.025 (0.066)	0.037 (0.055)
DEFAULT	-0.002 (0.342)	-0.005 (0.383)	-0.005 (0.668)	-0.003 (0.909)
RREL	-0.000 (0.494)	-0.001 (0.595)	-0.001 (0.742)	-0.000 (0.913)

Table 13: Log Dividend Growth on Climate with Controls 1995-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.001 (0.131)	0.001 (0.429)	0.002 (0.506)	0.003 (0.654)
VXO	-0.007 (0.164)	-0.020 (0.167)	-0.039 (0.156)	-0.069 (0.240)
TERM	0.002 (0.751)	0.007 (0.616)	0.010 (0.707)	0.011 (0.832)
DEFAULT	0.000 (0.988)	0.002 (0.886)	0.008 (0.786)	0.016 (0.772)
RREL	-0.000 (0.374)	-0.001 (0.362)	-0.003 (0.304)	-0.005 (0.411)

Table 14: Log Dividend Growth on Climate with Controls 1995-2012

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.000 (0.797)	0.001 (0.704)	0.001 (0.818)	0.003 (0.668)
VXO	-0.005 (0.099)	-0.015 (0.062)	-0.030 (0.066)	-0.042 (0.206)
TERM	0.005 (0.209)	0.014 (0.152)	0.030 (0.063)	0.036 (0.093)
DEFAULT	-0.003 (0.212)	-0.008 (0.223)	-0.011 (0.425)	-0.014 (0.602)
RREL	-0.000 (0.491)	-0.000 (0.796)	0.000 (0.938)	0.001 (0.879)

Table 15: Log Dividend Growth on Climate with Controls 2012-2022

Tables 13, 14, and 15 show that changes in the Climate Transition Risk Index do not affect future dividend growth for all different time horizons. This finding suggests that, similarly to what Brogaard and Detzel (2015) find for economic policy uncertainty, that price drops associated with increases in the Climate Transition Index can be explained by higher expected returns leading to expected dividends being discounted at a higher rate.

4.2.3 Forecasting Excess Returns & Macroeconomic Activity

Next, like Brogaard and Detzel (2015), I continue by investigating whether climate transition risks, as proxied by my index, have the ability to forecast excess returns or macroeconomic activity. Here I use the same variables as previously and again consider several different time horizons. Concretely, I estimate the expression shown in Equation (16).

$$y_{t,t+h} = \alpha + \beta \cdot CTI_t + \gamma' \cdot X_t + \epsilon_{t,t+h} \tag{16}$$

When excess stock and bond market returns are considered, the dependent variables denote the log excess returns during months $t+1$ through $t+h$, which can be computed by summing the different log excess returns. However, following Boons (2016), when the Industrial Production Index is used as the dependent variable, I make use of Equation (17).

$$y_{t,t+h} = \sum_{s=1}^{h} \log(\frac{IP_{t+s}}{IP_{t+s-1}}) \tag{17}$$

Likewise, when the CFNAI is used, the dependent variable is calculated as in Equation (18).

$$y_{t,t+h} = \sum_{s=1}^{h} CFNAI_{t+s} \tag{18}$$

Before continuing with the forecasting tests, it is important to recall the general negative sign found when considering the relation between changes in my measure of climate transition risks and contemporaneous returns and macroeconomic activity. Previously, authors such as Campbell and Yogo (2006) and Stambaugh (1999) have noted that variables that, in addition to showing this negative contemporaneous relation, are also highly persistent, can lead to forecasting bias. This forecasting bias can, in turn, lead to incorrect inference when testing the existence of predictability. To this end, I first test whether my index is stationary. I do this by making use of an Augmented Dickey–Fuller test to test the null hypothesis of a unit root being present.

Control	(1)
Test Statistic	-4.575
p-value	0.000

Table 16: Augmented Dickey–Fuller test

Table 16 shows the test statistic and corresponding p-value of this Augmented Dickey–Fuller test. Since the corresponding p-value is close to 0, it is possible to reject the H_0 of a unit root being present and conclude that the climate transition index is stationary.

Despite persistence not being a significant issue, following the example of Brogaard and Detzel (2015), I still take this bias into account. Similarly to them, I do this by making use of Hodrick (1992) standard errors. As Brogaard and Detzel (2015) state, these standard errors both account for conditional heteroskedasticity and the specific error structure resulting from overlapping time series. Authors such as Hodrick (1992) and Ang and Bekaert (2007) have shown that also in the presence of persistent regressors like dividend yields, as documented to be persistent by Koijen and Van Nieuwerburgh (2011), these standard errors show preferable statistical properties in comparison to Newey et al. (1987) standard errors. Namely, in such cases, Newey et al. (1987) standard errors often result in excessively rejecting the null hypothesis of no predictability.

4.2.3.1 Stock Returns

Tables 17, 18, and 19 show the coefficients corresponding to the different state variables from Equation (16) when excess stock market returns are used as the dependent variable, both for the entire period between 1995 and 2022 and for the sub-periods between 1995 and 2012, and between 2012 and 2022. Here, I consider four different time horizons, namely, 1 month ahead, 3 months ahead, 6 months ahead, and 12 months ahead.

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.478 (0.033)	0.746 (0.122)	1.052 (0.193)	1.165 (0.363)
VXO	-0.863 (0.010)	-3.577 (0.000)	-3.543 (0.000)	-2.440 (0.034)
TERM	-0.368 (0.109)	-0.333 (0.586)	0.389 (0.680)	0.238 (0.855)
DEFAULT	-0.097 (0.772)	-0.574 (0.549)	-5.320 (0.000)	-12.402 (0.000)
RREL	-0.119 (0.568)	-0.336 (0.515)	0.046 (0.961)	0.310 (0.870)
$\log(D/P)$	0.774 (0.005)	0.666 (0.351)	2.018 (0.100)	2.933 (0.088)

Table 17: Parameter Estimates Forecast Excess Stock Returns 1995-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.066 (0.947)	0.482 (0.443)	0.567 (0.425)	0.163 (0.793)
VXO	-1.249 (0.069)	-4.320 (0.000)	-3.150 (0.012)	-4.023 (0.000)
TERM	-0.341 (0.543)	-1.572 (0.079)	-1.948 (0.100)	1.228 (0.285)
DEFAULT	1.138 (0.399)	1.063 (0.485)	-5.064 (0.001)	-7.741 (0.000)
RREL	-0.820 (0.045)	-2.311 (0.007)	-3.765 (0.001)	-6.857 (0.000)
$\log(D/P)$	-0.088 (0.900)	-2.796 (0.101)	-1.625 (0.400)	-6.370 (0.004)

Table 18: Parameter Estimates Forecast Excess Stock Returns 1995-2012

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	1.076 (0.001)	1.972 (0.008)	2.373 (0.043)	3.276 (0.031)
VXO	-1.035 (0.005)	-4.254 (0.000)	-4.910 (0.000)	-3.310 (0.022)
TERM	-0.306 (0.259)	0.003 (0.997)	1.097 (0.338)	-0.083 (0.958)
DEFAULT	-0.233 (0.497)	-0.696 (0.513)	-4.983 (0.000)	-12.017 (0.000)
RREL	-0.123 (0.677)	-0.059 (0.934)	1.234 (0.262)	2.640 (0.170)
$\log(D/P)$	1.135 (0.000)	1.640 (0.026)	3.074 (0.010)	5.154 (0.002)

Table 19: Parameter Estimates Forecast Excess Stock Returns 2012-2022

Table 17 reveals a positive forecasting relation between my measure for climate transition risks and excess stock market returns for the entire period between 1995 and 2022 at a 5% significance level at a 1-month horizon. However, Table 18 shows that this forecasting relation did not exist during the period between 1995 and 2012. Instead, as Table 19 shows, this predictive power of my measure of climate transition risks only appears to exist in more recent years. Furthermore, when only considering the period between 2012 and 2022, the forecasting relation exists not only for the 1-month time horizon but also for the 3-month, 6-month, and 12-month horizons. This can be interpreted as only in recent years that investors have begun to see increases in climate transition risks leading to a higher perceived risk in stock markets. This signals that investors now require increased compensation for taking on this additional risk.

4.2.3.2 Bond Returns

Tables 20, 21, and 22 show the coefficients corresponding to the different state variables from Equation (16) when excess bond market returns are used as the dependent variable, both for the entire period between 1995 and 2022 and for the sub-periods between 1995 and 2012, and between 2012 and 2022. Again, I consider four different time horizons, namely, 1 month ahead, 3 months ahead, 6 months ahead, and 12 months ahead.

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.002 (0.816)	-0.010 (0.628)	0.227 (0.000)	0.256 (0.001)
VXO	0.019 (0.014)	0.058 (0.007)	-0.195 (0.000)	-0.126 (0.148)
TERM	0.066 (0.000)	0.202 (0.000)	-0.197 (0.000)	-0.538 (0.000)
DEFAULT	-0.025 (0.000)	-0.082 (0.000)	-0.010 (0.791)	-0.269 (0.000)
RREL	-0.007 (0.357)	0.006 (0.784)	0.063 (0.036)	0.179 (0.006)
$\log(D/P)$	0.023 (0.000)	0.070 (0.000)	-0.125 (0.000)	-0.247 (0.000)

Table 20: Parameter Estimates Forecast Excess Bond Returns 2003-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.013 (0.160)	-0.040 (0.133)	0.124 (0.000)	0.003 (0.004)
VXO	0.009 (0.407)	0.037 (0.170)	-0.200 (0.000)	0.000 (0.634)
TERM	0.067 (0.000)	0.204 (0.000)	0.099 (0.002)	0.006 (0.013)
DEFAULT	-0.016 (0.004)	-0.060 (0.000)	0.277 (0.000)	-0.003 (0.031)
RREL	-0.031 (0.000)	-0.063 (0.000)	0.014 (0.611)	0.000 (0.628)
$\log(D/P)$	0.020 (0.000)	0.060 (0.000)	0.025 (0.134)	-0.002 (0.010)

Table 21: Parameter Estimates Forecast Excess Bond Returns 2003-2012

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.050 (0.000)	0.141 (0.000)	0.517 (0.000)	1.004 (0.000)
VXO	-0.005 (0.748)	-0.023 (0.617)	-0.084 (0.301)	-0.244 (0.077)
TERM	0.081 (0.000)	0.250 (0.000)	-0.312 (0.000)	-0.645 (0.000)
DEFAULT	0.011 (0.183)	0.032 (0.185)	0.002 (0.968)	0.067 (0.473)
RREL	-0.006 (0.267)	0.005 (0.745)	-0.055 (0.341)	-0.138 (0.266)
$\log(D/P)$	0.021 (0.000)	0.065 (0.000)	-0.178 (0.000)	-0.355 (0.000)

Table 22: Parameter Estimates Forecast Excess Bond Returns 2012-2022

Similarly to what is seen for excess stock returns, Table 20 reveals a positive forecasting relation between my measure for climate transition risks and excess bond market returns for the entire considered time period at a 5% significance level at both a 6-month horizon and 12-month horizon. As Table 21 reveals, this relationship already existed between 2003 and 2012. Furthermore, as is the case for excess stock market returns, the forecasting relation for my measure of climate transition risks becomes stronger between 2012 and 2022, as Table 22 shows. Not only do the coefficient estimates for the 6-month and 12-month horizon increase, but also the coefficients for the 1-month and 12-month horizon become positive and statistically significant at a 5% significance level. This suggests that also in bond markets, especially in recent years, investors require additional compensation for carrying climate transition-related risks.

4.2.3.3 Macroeconomic Activity

Tables 23, 24, and 25 show the coefficients corresponding to the different state variables from Equation (16) when the CFNAI is used as the dependent variable, both for the entire period considered between 1995 and 2022 and for the sub-periods between 1995 and 2012, and between 2012 and 2022. Similarly, Tables 26, 27, and 28 show the coefficients corresponding to the different state variables from Equation (16) when the Industrial Production Index is used as the dependent variable.

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.012 (0.766)	0.115 (0.145)	0.142 (0.161)	0.058 (0.776)
VXO	-0.060 (0.419)	-0.004 (0.960)	0.156 (0.426)	-0.168 (0.467)
TERM	0.125 (0.283)	0.322 (0.060)	0.417 (0.010)	-0.189 (0.412)
DEFAULT	-0.304 (0.003)	-1.011 (0.000)	-1.866 (0.000)	-2.504 (0.000)
RREL	0.152 (0.193)	0.504 (0.007)	1.019 (0.000)	1.512 (0.000)
$\log(D/P)$	-0.091 (0.000)	-0.207 (0.000)	-0.382 (0.000)	-0.791 (0.000)

Table 23: Parameter Estimates CFNAI 1995-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.070 (0.517)	0.192 (0.337)	0.339 (0.120)	0.948 (0.531)
VXO	-0.236 (0.398)	-0.235 (0.397)	0.092 (0.879)	-0.613 (0.264)
TERM	-0.035 (0.871)	0.197 (0.635)	0.715 (0.048)	1.183 (0.000)
DEFAULT	-0.536 (0.289)	-1.448 (0.018)	-2.239 (0.000)	-2.700 (0.000)
RREL	0.159 (0.719)	0.523 (0.400)	1.219 (0.022)	2.087 (0.000)
$\log(D/P)$	-0.268 (0.141)	-0.403 (0.055)	-0.379 (0.085)	-0.386 (0.046)

Table 24: Parameter Estimates Forecast CFNAI 1995-2012

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.026 (0.373)	-0.026 (0.674)	-0.082 (0.404)	-0.487 (0.040)
VXO	-0.006 (0.881)	-0.025 (0.728)	0.013 (0.915)	-0.213 (0.481)
TERM	0.109 (0.000)	0.267 (0.000)	0.261 (0.003)	-0.693 (0.002)
DEFAULT	-0.273 (0.000)	-0.830 (0.000)	-1.555 (0.000)	-1.991 (0.000)
RREL	0.161 (0.000)	0.486 (0.000)	0.897 (0.000)	1.137 (0.000)
$\log(D/P)$	-0.071 (0.000)	-0.215 (0.000)	-0.439 (0.000)	-0.915 (0.000)

Table 25: Parameter Estimates Forecast CFNAI 2012-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.000 (0.938)	0.001 (0.210)	0.001 (0.369)	-0.002 (0.295)
VXO	0.000 (0.897)	0.001 (0.397)	0.004 (0.047)	0.004 (0.105)
TERM	0.002 (0.074)	0.004 (0.007)	0.007 (0.000)	0.005 (0.017)
DEFAULT	-0.003 (0.002)	-0.009 (0.000)	-0.018 (0.000)	-0.025 (0.000)
RREL	0.001 (0.186)	0.004 (0.013)	0.009 (0.000)	0.013 (0.000)
$\log(D/P)$	-0.001 (0.001)	-0.002 (0.000)	-0.004 (0.000)	-0.008 (0.000)

Table 26: Parameter Estimates Industrial Production 1995-2022

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	-0.001 (0.569)	0.000 (0.872)	-0.000 (0.940)	-0.000 (0.888)
VXO	-0.002 (0.340)	-0.002 (0.305)	-0.001 (0.920)	-0.006 (0.235)
TERM	0.000 (0.845)	0.002 (0.544)	0.007 (0.044)	0.013 (0.000)
DEFAULT	-0.005 (0.247)	-0.013 (0.014)	-0.019 (0.000)	-0.024 (0.000)
RREL	0.001 (0.754)	0.005 (0.373)	0.012 (0.010)	0.021 (0.000)
$\log(D/P)$	-0.002 (0.101)	-0.004 (0.013)	-0.005 (0.004)	-0.008 (0.000)

Table 27: Parameter Estimates Forecast Industrial Production 1995-2012

Control	1 Month	3 Months	6 Months	12 months
CLIMATE	0.000 (0.429)	0.002 (0.540)	0.003 (0.490)	-0.001 (0.799)
VXO	0.001 (0.169)	0.002 (0.199)	0.004 (0.004)	0.006 (0.042)
TERM	0.001 (0.000)	0.004 (0.000)	0.005 (0.000)	0.000 (0.938)
DEFAULT	-0.003 (0.000)	-0.008 (0.000)	-0.017 (0.000)	-0.023 (0.000)
RREL	0.002 (0.000)	0.005 (0.000)	0.009 (0.000)	0.012 (0.000)
$\log(D/P)$	-0.000 (0.100)	-0.002 (0.000)	-0.004 (0.000)	-0.008 (0.000)

Table 28: Parameter Estimates Forecast Industrial Production 2012-2022

Tables 23 up to 28 show that climate transition risks, as measured by the Climate Transition Index, generally do not significantly forecast macroeconomic activity as measured by the CFNAI or the Industrial Production Index. The only exception corresponds to the CFNAI at the 12-month horizon for the period between 2012 and 2022. Here an increase in climate transition risks seems to forecast a decrease in the CFNAI at a 5% significance level.

In conclusion, although there is little evidence for climate transition risks being able to forecast macroeconomic activity, my climate transition index does have the ability to predict excess stock and bond market returns. This finding still opens the door for climate transition risks as a candidate factor for commanding a risk premium.

4.3 Climate Transition Risk Premium Via Portfolio Sorts

With my measure of climate transition risks, thus having forecasting power for excess stock and bond market returns, the next natural step is to directly investigate whether climate transition-related risks proxied by my index command a risk premium in the cross-section of U.S. stock and both long-term and short-term bond markets. Similarly to authors such as Huynh and Xia (2021), Faccini et al. (2021), Bats et al. (2023) and Bali, Brown, and Tang (2017), and Brogaard and Detzel (2015), I will seek to answer this research question via portfolio sorts. As shown by Bali et al. (2016) and Cattaneo et al. (2022), portfolio sorts can be seen as a two-step non-parametric estimator of the significance of asset-pricing factors that is able to discover potential non-linear relations between returns and asset-pricing factors.

Recall that it is, in fact, shocks to risk factors that command risk premia. This means that in order to discover the existence of a climate transition risk premium as implied by my Climate Transition Index, I first need to find shocks to Climate Transition Index. In order to obtain these innovations to climate transition risks, I estimate an AR(p) process for my climate index. Following Campbell and Yogo (2006) and Brogaard and Detzel (2015), I make use of the lag order that minimizes the Bayesian Information Criterion. This minimization occurs when using lags 1, 3, and 10 with a corresponding BIC equal to 3090.558. Hence, I estimated the AR model from Equation (19).

$$CTI_t = \gamma_0 + \gamma_1 \cdot CTI_{t-1} + \gamma_2 \cdot CTI_{t-3} + \gamma_3 \cdot CTI_{t-10} + \epsilon_t^{CTI} \tag{19}$$

This yields the estimates shown in Table 29.

Parameter	Estimate
γ_0	14.820 (0.002)
γ_1	0.609 (0.000)
γ_2	0.167 (0.000)
γ_3	0.076 (0.070)

Table 29: AR Coefficient Estimates Climate Index

Next, by reversing Equation (19) using the parameter estimates of Table 29, I can recover the innovations to the climate index, ϵ_t^{CTI}, and start the portfolio sort procedure to test whether climate transition risks are priced. Figure 2 shows the recovered innovations, ϵ_t^{CTI}.

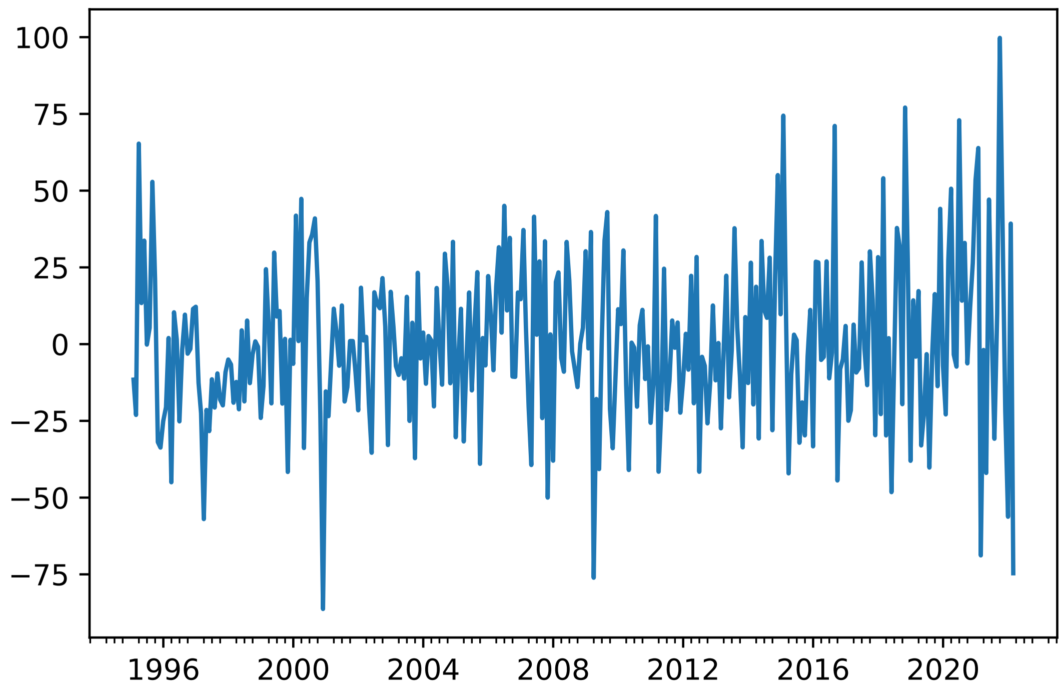


Figure 2: Innovations to Climate Transition Index, ϵ_t^{CTI}

With the climate transition news shocks recovered it becomes possible to start the portfolio sorting procedure. During the first step of this procedure, I estimate the time-varying exposure to innovations in climate transition risks for excess returns of different assets by using backward-looking rolling window regressions of asset returns using a 36-month window. As Cattaneo et al. (2022) remark, with portfolio sorts, the choice for the estimation window with portfolio sorts can be seen as a tuning parameter involving a trade-off between bias and variance. A 36-month window means a shorter window than the five-year window that, as Cattaneo et al. (2022) note, is often used in practice. This choice is made due to the limited size of the available data and to reduce computational resources that are needed with larger window sizes. It is not investigated if the conclusions reached on the existence of a climate transition risk premium are sensitive to the choice for the estimation window, and this question remains open for further investigation by other researchers. Concretely, I estimate Equation (20) for each asset.

$$r_{i,t}^e = \alpha_i + \beta_{CTI} \cdot \epsilon_t^{CTI} + \boldsymbol{\beta} \cdot \boldsymbol{Z_t} + \nu_t \tag{20}$$

In Equation (20) $r_{i,t}^e$ are stock or bond returns above the one-month Treasury bill rate, ϵ_t^{CTI} are the innovations to the climate index, and Z_t are common controls that are well-established in academic literature to explain the cross-section of stock returns or bond returns. For stock returns, this includes the three factors of Fama and French (1993) (the excess market return, the Small Minus Big Factor, and High Minus Low Factor), the five factors of Fama and French

(2015), which expands on the three-factor model by including the Robust Minus Weak Factor and Conservative Minus Aggressive Factor, and the five-factor model augmented with the momentum factor by Carhart (1997). Regarding bond returns, I follow Chung, Wang, and Wu (2019) and use the term and default spreads and market volatility measured by the Chicago Board Options Exchange Market Volatility Index as controls.

I continue the portfolio sort approach by rolling forward the starting period with a single month and sorting the assets in quintile portfolios. For each portfolio, I subsequently calculate the post-sorting equally weighted monthly return. Moreover, I also calculate the return of a long-short spread by subtracting the return of the first portfolio from the return of the fifth portfolio. I continue this procedure until the sample is exhausted. Subsequently, considering that a long-short spread portfolio is also an excess return, I can use these spread portfolios to gauge whether there is a statistically significant compensation for exposure to climate transition risks that other commonly used asset-pricing factors cannot explain. I do this by investigating whether α_i for the spread portfolios is significantly different from zero.

4.3.1 Equities

Tables 30, 31, and 32 show the α-estimates for the portfolios corresponding to the various periods considered. The corresponding Newey et al. (1987) standard errors are shown in parentheses. For this analysis, I use all stocks listed on the $S\&P$ 500 Index between 1995 and 2022. Here, I control for exposure to excess market returns, the three factors by Fama and French (1993), the five factors by Fama and French (2015), and the five factors by Fama and French (2015) augmented with the momentum factor by Carhart (1997).

Alpha	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	0.327 (0.109)	0.258 (0.109)	0.145 (0.313)	0.241 (0.050)
Second	0.085 (0.625)	0.023 (0.842)	-0.139 (0.149)	-0.082 (0.348)
Third	-0.027 (0.845)	-0.078 (0.457)	-0.221 (0.022)	-0.168 (0.075)
Fourth	0.064 (0.677)	0.008 (0.946)	-0.150 (0.123)	-0.103 (0.268)
Fifth	0.023 (0.883)	-0.032 (0.802)	-0.081 (0.535)	-0.021 (0.872)
Spread	-0.304 (0.059)	-0.290 (0.063)	-0.226 (0.145)	-0.263 (0.081)

Table 30: Alpha Estimates 1995-2022

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	-0.261 (0.140)	-0.154 (0.346)	-0.195 (0.206)	-0.089 (0.563)
SECOND	-0.380 (0.067)	-0.330 (0.008)	-0.323 (0.006)	-0.310 (0.011)
THIRD	-0.255 (0.150)	-0.220 (0.059)	-0.217 (0.049)	-0.209 (0.074)
FOURTH	-0.257 (0.131)	-0.229 (0.051)	-0.224 (0.044)	-0.201 (0.063)
FIFTH	-0.252 (0.225)	-0.194 (0.210)	-0.207 (0.168)	-0.167 (0.270)
SPREAD	0.009 (0.966)	-0.040 (0.849)	-0.012 (0.954)	-0.079 (0.701)

Table 31: Alpha Estimates 1995-2012

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	0.718 (0.014)	0.542 (0.008)	0.376 (0.055)	0.437 (0.006)
SECOND	0.347 (0.151)	0.217 (0.159)	-0.048 (0.731)	-0.006 (0.962)
THIRD	0.098 (0.620)	-0.013 (0.935)	-0.257 (0.085)	-0.217 (0.114)
FOURTH	0.224 (0.309)	0.088 (0.584)	-0.139 (0.341)	-0.105 (0.436)
FIFTH	0.195 (0.392)	0.049 (0.803)	-0.011 (0.956)	0.032 (0.868)
SPREAD	-0.522 (0.017)	-0.493 (0.011)	-0.387 (0.069)	-0.405 (0.050)

Table 32: Alpha Estimates 2012-2022

Table 30 shows the α-estimates for the various spread portfolios when controlling for standard financial factors. This table shows that the coefficients corresponding to α for the spread portfolios are always negative, but not for all specifications significant at even a 10% significance level. This lack of significance means that when the entire period between 1995 and 2022 is considered, there is insufficient evidence to reject the null hypothesis of the climate transition factor not being priced.

However, an interesting pattern emerges when conducting a sub-sample investigation into the period between 1995 and 2012 and between 2012 and 2022. As shown in Table 31, for the period between 2012 and 2022, the estimated coefficients for α of the spread portfolios, when controlling for the different factors, are all not significantly different from zero. However, another picture emerges when considering the final period starting from 2012, as shown in Table 32. Namely, during this period, when controlling for the different financial factors, the α-estimates are all negative and significant at a 10% significance level. Furthermore, except when controlling for the five factors by Fama and French (2015), the α-estimates are even significant at a 5% significance level. This indicates the emergence of a climate transition risk premium in recent years. This matches the findings by authors such as Faccini et al. (2021) and Bolton and Kacperczyk (2021).

Furthermore, the α-estimates on the spread portfolios over the entire period and between 2012 and 2022 are all negative. This is consistent with an intertemporal hedging motive related to climate transition risks in the vein of the intertemporal hedging hypothesis by Merton (1973). In this context, this entails, similarly to what Faccini et al. (2021) find, that stocks that display a negative correlation with shocks to climate transition news tend to be associated with higher levels of risk since an increase in the climate transition factor signifies an unexpected rise in climate transition risks. In order to mitigate this risk, investors opt to purchase stocks with positive climate transition betas. Consequently, the demand for these stocks increases, driving up their prices while simultaneously reducing their returns.

4.3.2 Short-Term Bond Returns

Next, Tables 33, 34, and 35 show the corresponding α-estimates for the different spread portfolios for several different periods using short-term bonds. Following Bats et al. (2023), short-term bonds are defined as bonds with times to maturities of up to seven years. Furthermore, like Bats et al. (2023), I calculate the return of a short-term bond as shown in Equation (21).

$$r_{i,t} = \frac{(P_{i,t} + AI_{i,t}) + C_{i,t} - (P_{i,t-1} + AI_{i,t-1})}{(P_{i,t-1} + AI_{i,t-1})} \tag{21}$$

In Equation (21), $P_{i,t}$ stands for the price of a bond, $AI_{i,t}$ stands for the accrued interest, and $C_{i,t}$ stands for the coupon payment. Finally, the one-month Treasury bill rate is subtracted from $r_{i,t}$ to obtain the excess bond return, $r^e_{i,t}$. Like, Bats et al. (2023), I use the factors used by Chung et al. (2019) as controls. In Tables 33, 34, and 35, the columns labeled (1) indicate controlling for excess market returns, the default spread, and the term spread. The columns labeled (2) additionally indicate accounting for VXO, the implied volatility series on the $S\&P$ 100 index. Finally, the columns labeled (3) also indicate taking the size factor and the book-to-market ratio factor by Fama and French (1993) into account. As Bats et al. (2023) state, this additional use of stock market factors is done to align with existing corporate bond market literature.

	(1)	(2)	(3)
FIRST	-0.295 (0.646)	0.397 (0.555)	0.469 (0.494)
SECOND	-0.518 (0.382)	0.191 (0.755)	0.279 (0.661)
THIRD	-0.184 (0.749)	0.552 (0.386)	0.671 (0.301)
FOURTH	-0.608 (0.319)	0.326 (0.564)	0.423 (0.463)
FIFTH	-0.772 (0.182)	0.157 (0.776)	0.252 (0.651)
SPREAD	-0.457 (0.032)	-0.222 (0.503)	-0.192 (0.544)

Table 33: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	-0.218 (0.809)	1.118 (0.271)	1.190 (0.212)
SECOND	0.108 (0.880)	1.637 (0.018)	1.674 (0.014)
THIRD	-0.079 (0.911)	1.519 (0.133)	1.624 (0.106)
FOURTH	0.296 (0.729)	2.558 (0.003)	2.652 (0.003)
FIFTH	-0.719 (0.474)	1.544 (0.197)	1.653 (0.149)
SPREAD	-0.506 (0.268)	0.422 (0.620)	0.467 (0.550)

Table 34: Alpha Estimates 2003-2012

	(1)	(2)	(3)
FIRST	-0.222 (0.744)	0.853 (0.284)	0.850 (0.339)
SECOND	-0.685 (0.305)	0.305 (0.711)	0.507 (0.583)
THIRD	-0.409 (0.522)	0.642 (0.388)	0.775 (0.360)
FOURTH	-0.542 (0.417)	0.463 (0.558)	0.555 (0.528)
FIFTH	-0.756 (0.234)	0.200 (0.772)	0.418 (0.594)
SPREAD	-0.534 (0.003)	-0.653 (0.001)	-0.433 (0.038)

Table 35: Alpha Estimates 2012-2022

Table 33 shows that for the entire period between 2003 and 2022, climate transition risks only earn a significant negative excess return at a 5% significance level when controlling for the excess market returns, the default spread, and the term spread. However, the significance disappears after additionally controlling for VXO and when controlling for the VXO and the size and book-to-market factors. Furthermore, Table 34 shows that for the sub-period between 2003 and 2012, the excess return on the spread portfolios is insignificant when controlling for any of the different sets of controls. Moreover, when controlling for VXO and when controlling for the VXO and the size and book-to-market factors, the α-estimates of the spread portfolios even become positive. Finally, Table 35 reveals that only when considering the period between 2012 and 2022 will the excess return on the spread portfolios become significant, controlling for all variables considered. In addition, all different α-estimates are also negative. This matches what is seen for stock returns in the previous section, namely the emergence of a climate transition risk premium only in recent years for U.S. corporate short-term bond markets. This can again be explained by a hedging explanation related to climate transition-related risks along the lines of the intertemporal hedging hypothesis by Merton (1973). This finding contrasts somewhat with findings by Bats et al. (2023) for the E.U. short-term corporate bond market. They find that since the Paris Agreement, only physical climate risk is significantly priced in E.U. corporate bond markets. However, they do not find evidence for the existence of a statistically significant E.U. climate transition risk premium.

4.3.3 Long-Term Bond Returns

Finally, I also investigate the existence of a climate transition risk premium in U.S. corporate long-term bond markets. Again, following Bats et al. (2023), bonds with times to maturities longer than seven years are classified as long-term bonds. Tables 36, 37, and 38 show the corresponding α-estimates for the different spread portfolios for several different periods using long-term bonds. The returns for the long-term bonds are calculated the same way as the short-term bonds, as shown in Equation (21). Likewise, in Tables 36, 37, and 38, the columns labeled (1) indicate controlling for excess market returns, the default spread, and the term spread. The columns labeled (2) additionally indicate accounting for VXO, the implied volatility series on the $S\&P$ 100 index. Finally, the columns labeled (3) also indicate taking the size factor and the book-to-market ratio factor by Fama and French (1993) into consideration. This additional use of stock market factors is again done to align with existing corporate bond market literature.

	(1)	(2)	(3)
FIRST	0.094 (0.367)	0.264 (0.009)	0.265 (0.007)
SECOND	0.001 (0.992)	0.099 (0.110)	0.106 (0.093)
THIRD	-0.015 (0.757)	0.061 (0.235)	0.069 (0.188)
FOURTH	-0.032 (0.506)	0.030 (0.532)	0.039 (0.423)
FIFTH	-0.159 (0.032)	-0.107 (0.143)	-0.097 (0.192)
SPREAD	-0.253 (0.000)	-0.370 (0.000)	-0.362 (0.000)

Table 36: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.057 (0.644)	0.444 (0.037)	0.448 (0.023)
SECOND	-0.016 (0.829)	0.217 (0.017)	0.222 (0.016)
THIRD	-0.015 (0.830)	0.174 (0.027)	0.180 (0.021)
FOURTH	-0.005 (0.949)	0.148 (0.105)	0.156 (0.070)
FIFTH	0.020 (0.899)	0.122 (0.493)	0.135 (0.413)
SPREAD	-0.037 (0.863)	-0.322 (0.294)	-0.312 (0.264)

Table 37: Alpha Estimates 2003-2012

	(1)	(2)	(3)
FIRST	0.231 (0.032)	0.382 (0.000)	0.382 (0.000)
SECOND	0.020 (0.646)	0.073 (0.102)	0.075 (0.095)
THIRD	-0.025 (0.315)	0.003 (0.900)	0.005 (0.845)
FOURTH	-0.070 (0.004)	-0.052 (0.040)	-0.050 (0.051)
FIFTH	-0.324 (0.000)	-0.296 (0.000)	-0.295 (0.000)
SPREAD	-0.555 (0.000)	-0.679 (0.000)	-0.677 (0.000)

Table 38: Alpha Estimates 2012-2022

Table 36 shows that for the entire period between 2003 and 2022, climate transition risks earn a significant negative excess return when controlling for all different control factors. This is somewhat in contrast with what is found for short-term bonds. However, in alignment with the short-term bonds, Table 37 shows that for the sub-period between 2003 and 2012, the excess returns on the spread portfolios for the long-term bonds are again not statistically significant. Instead, as is the case in equity and short-term bond markets, the existence of a climate transition risk premium for long-term bonds hinges on more recent years. Namely, Table 38 reveals that only when considering the period between 2012 and 2022 do the excess returns on the spread portfolios become negative and significant at a 5% significance level when controlling for all different variables considered. This statistically significant risk premium for U.S. corporate bond markets again clashes with what Bats et al. (2023) find for E.U. corporate bond markets. Namely, as is the case with short-term bond markets, Bats et al. (2023) find only a significant risk premium associated with physical climate risks but not climate transition risks.

4.3.4 Individual Newspapers

In this section, I conduct additional robustness tests and see whether the found existence of a climate transition risk premium in U.S. equity and bond markets still exists when separately considering the individual newspapers from which I construct my index. To this end, I use the separate newspaper-specific indices I used when constructing the final climate transition index. Again, I recover the shocks from these indices by estimating an AR model with the optimal amount of lags selected using the Bayes Information Criterion. These shocks are shown in Figures 3, 4, and 5.

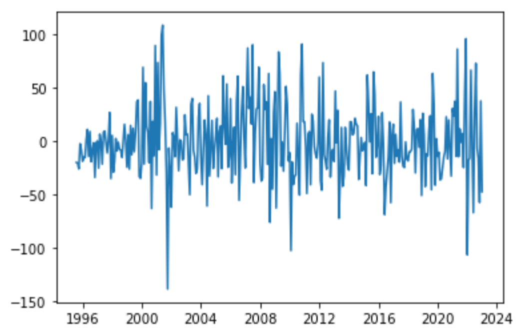


Figure 3: Innovations to WSJ Climate Transition Index, ϵ_t^{WSJI}

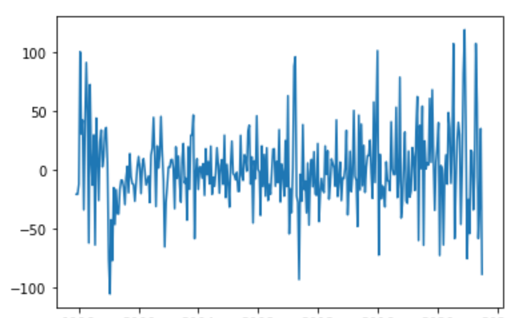


Figure 4: Innovations to NYT Climate Transition Index, ϵ_t^{NYTI}

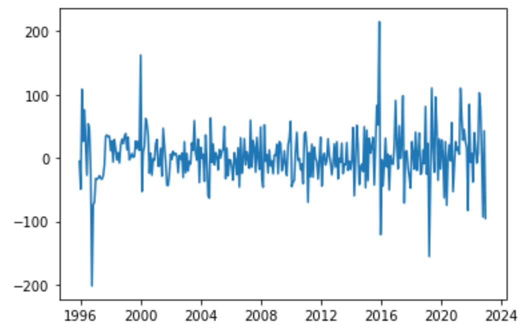


Figure 5: Innovations to WP Climate Transition Index, ϵ_t^{WPI}

With these shocks for the individual newspaper indices, I repeat the procedure previously described. Tables 43 up to 51 show the unexplained excess stock returns of the spread portfolios when controlling for various factors for the different newspapers. Here it is noticeable that only the shocks to the Washington Post Index seem to command a risk premium over the entire period, as shown in Table 49. However, Tables 50 and 51 reveal that this is again mainly caused by the final period between 2012 and 2022, considering that the results corresponding to the period between 1995 and 2012 from Table 50 show that the α of the spread portfolios are never significant when controlling for the different factors.

Furthermore, Tables 43 up to 48 reveal that when only shocks to the NYT and WSJ Indices are considered, no significant risk premium exists in stock markets stemming from climate transition risks. For these shocks, all α-estimates for the spread portfolios are insignificant for both the entire period between 1995 and 2022 and the subperiods 1995-2012 and 2012-2022 at a 5% significance level. This would suggest that the existence of a climate transition risk premium found when taking articles from all the different sources into account is caused by the articles from the Washington Post.

Next, Tables 52 up to 60 show the unexplained excess short-term bond returns. Table 52 reveals that over the entire time period, only the shocks to the WSJ Index command a significant risk premium. Tables 53 and 54 indicate that the existence of a risk premium is again mainly driven by the period between 2012 and 2022. Tables 55 up to 60 show that the shocks to the New York Times Index and the Washington Post Index do not command a risk premium when considering the significance of the α-estimates for the spread portfolios over the entire period. However, when only looking at the period between 2012 and 2012, the unexplained return on the spread portfolios is again significant when controlling for the different factors. Overall this corresponds with the findings reached when considering the multi-paper index of a recently emerged climate transition risk premium in short-term bond markets.

Finally, considering the long-term bonds, Tables 61 up to 69 reveal that the different separate indices lead to the same conclusion as is reached when looking at the multi-paper index. Namely, the shocks to all three separate indices seem to command a significant risk premium over the entire period between 2003 and 2022, as is the case for the shocks to the multi-paper index. Furthermore, the results for all three different sub-indices also seem to hinge on the second sub-period between 2012 and 2022, as the unexplained returns of the spread portfolios are insignificant when controlling for the different sets of factors in the first sub-sample.

Overall this indicates that the existence of a climate transition risk premium does not hinge on the contribution of one particular newspaper. For the short-term bond returns, the existence of a climate transition risk premium over the entire period considered seems to depend on a single newspaper. However, closer inspection reveals that for the different assets considered, the individual indices generally point towards no such risk premium existing between 2003 and 2012 and that this risk premium only appears in the later years between 2012 and 2022. This is in line with the conclusion that is reached when considering the multi-paper index. The exception is when considering the WSJ and NYT indices for excess stock market returns, as those indices also do not indicate the existence of a climate transition risk premium after 2012.

4.4 Climate Transition Risk Premium Via Dynamic Conditional Correlation

I conduct a further robustness test for the existence of a climate transition risk premium by following the approach of Bali and Engle (2010). This approach makes use of the Dynamic Conditional Correlation (DCC) model created by Engle (2002) to estimate the time-varying conditional covariances between the shocks to the Climate Transition Index and excess monthly returns of individual stock and bond returns and a number of test portfolios. Subsequently, these conditional covariances are used to analyze how stocks' excess returns react to their conditional covariances with climate transition risks when controlling for different macroeconomic or financial factors.

The DCC model by Engle (2002) overcomes the limitations of conventional approaches that assume constant correlations between assets. It acknowledges that correlations among assets can vary over time due to market conditions and dynamics. DCC parameterizes the volatilities and correlations separately and has the following general specification shown in Equation (22).

$$y_{t+1} = \begin{pmatrix} r^i_{t+1} \\ r^m_{t+1} \\ x_{t+1} \end{pmatrix} = \alpha_0 + \alpha_1 y_t + \mu_t + \epsilon_{t+1} \tag{22}$$

For the asset returns, r^i_{t+1}, μ_t follows from Equation (11), since $\mu_{t+1} = E_t(r^i_{t+1}) = r^f_t + A\ Cov_t(r^i_{t+1}, r^m_{t+1}) + B\ Cov_t(r^i_{t+1}, \Delta x_{t+1})$. Furthermore, the variance-covariance matrix of ϵ_{t+1} is given by the expression shown in Equation (23).

$$V_t(\epsilon_{t+1}) = D_{t+1}\rho_{t+1}D_{t+1} \tag{23}$$

Here D_{t+1} is a diagonal matrix of conditional standard deviations given by Equation (24).

$$D^2_{t+1} = \beta_0 + \beta_1 y^2_t + \beta_2 D^2_t \tag{24}$$

Furthermore, the correlations from Equation (23) are given by Equation (25).

$$\rho_t = diag(Q_t)^{-\frac{1}{2}} \quad Q_t \quad diag(Q_t)^{-\frac{1}{2}} \tag{25}$$

In Equation (25), $Q_{t+1} = \bar{\rho} + \gamma_1 \cdot (u_t u_t' - \bar{\rho}) + \gamma_2(Q_t - \bar{\rho})$, with $u_t = D_t^{-1}\epsilon_t$ and $\bar{\rho} = \frac{1}{T}\sum_{t=1}^{T} u_t u_t'$

Next, following Bali and Engle (2010), the estimation procedure continues by removing autoregressive components in the returns, and individual univariate GARCH models are estimated for each return and state variable. Next bivariate DCC estimates of correlations are calculated for each individual return or test portfolio with the market return, as well as with various state variables, including the climate factor. This is accomplished using the bivariate likelihood function, as Bali and Engle (2010) state. Finally, the expected return equation is estimated using panel regression, where the various conditional covariances serve as regressors.

In particular, following Bali and Engle (2010), I estimate the following equations via seemingly unrelated regression (SUR) while constraining all regressions to have the same slope coefficient as is done in Equation (26) and in Equation (27).

$$\begin{aligned} r_{t+1}^{i} - r_t^f &= C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,\Delta DEF,t+1} + B_2 \cdot \sigma_{i,\Delta TERM,t+1} \\ &+ B_3 \cdot \sigma_{i,\Delta FED,t+1} + B_4 \cdot \sigma_{i,\epsilon^{CTI},t+1} + \epsilon_{i,t+1} \end{aligned} \tag{26}$$

$$\begin{aligned} r_{t+1}^{i} - r_t^f &= C_i + A \cdot \sigma_{im,t+1} + B_1 \cdot \sigma_{i,SMB,t+1} + B_2 \cdot \sigma_{i,HML,t+1} \\ &+ B_3 \cdot \sigma_{i,RMW,t+1} + B_4 \cdot \sigma_{i,CMA,t+1} \\ &+ B_5 \cdot \sigma_{i,MOM,t+1} + B_6 \cdot \sigma_{i,\epsilon^{CTI},t+1} + \epsilon_{i,t+1} \end{aligned} \tag{27}$$

In Equations (26) and (27), r_{t+1}^i are individual stocks or portfolio returns, r_t^f is the U.S. 1 Month Treasury Bill Rate, C_i is an asset-specific intercept, and A and the B terms are common slope coefficients. Furthermore, $\sigma_{im,t+1}$, $\sigma_{i,\Delta DEF,t+1}$, $\sigma_{i,\Delta TERM,t+1}$, $\sigma_{i,\Delta FED,t+1}$, $\sigma_{i,SMB,t+1}$, $\sigma_{i,HML,t+1}$, $\sigma_{i,RMW,t+1}$, $\sigma_{i,CMA,t+1}$, $\sigma_{i,MOM,t+1}$, $\sigma_{i,\epsilon^{CTI},t+1}$ are the conditional time-varying covariance estimated via DCC between the excess returns on the assets and respectively, the market return, changes in the default spread, changes in the term spread, changes in the federal funds rate, the five factors by Fama and French (2015), the momentum factor by Carhart (1997) and shocks to the climate transition index.

The results from running the regression from Equation (26) when using the individual stock returns, individual long-term bonds, and a number of research portfolios from French (2023) are shown in Tables 39, 40, and 41.

	$\sigma_{im,t+1}$	$\sigma_{i,\Delta DEF,t+1}$	$\sigma_{i,\Delta TERM,t+1}$	$\sigma_{i,\Delta FED,t+1}$	$\sigma_{i,\epsilon^{CTI},t+1}$
Individual Stocks	3.654 (0.000)	-2.140 (0.000)	-0.228 (0.000)	-6.637 (0.000)	-0.426 (0.000)
Long-Term Bonds	3.913 (0.000)	-10.347 (0.000)	-4.971 (0.000)	-1.766 (0.078)	-0.391 (0.000)
48 Industry Portfolios	3.331 (0.000)	0.666 (0.000)	5.148 (0.000)	5.773 (0.000)	-0.130 (0.051)
Size/Investment Sorted	2.468 (0.000)	0.304 (0.000)	2.017 (0.000)	2.289 (0.000)	-0.419 (0.000)
Momentum Sorted	4.680 (0.000)	0.736 (0.000)	3.340 (0.000)	5.078 (0.000)	-0.073 (0.249)
Size/B-M Sorted	7.104 (0.000)	-0.140 (0.000)	0.718 (0.002)	1.426 (0.000)	-0.027 (0.241)

Table 39: Risk premia induced by conditional covariation with macroeconomic variables.

Table 40 shows the estimates for the risk premia induced by conditional covariation with macroeconomic variables and shocks to the climate transition index. As Bali and Engle (2010) find, the common slope coefficient A on $\sigma_{im,t+1}$ is for the different assets and portfolios used both positive and highly significant. Furthermore, my estimates for A are generally with values between 2.468 and 4.680, in the same range as the estimates reported by Bali and Engle (2010). Only the estimate on the portfolios sorted by size and book-to-market is considerably higher, with an estimate of 7.104. Furthermore, like Bali and Engle (2010), I also find that the slope coefficients on $\sigma_{i,\Delta DEF,t+1}$ and $\sigma_{i,\Delta TERM,t+1}$ are highly significant. However, unlike Bali and Engle (2010), my estimates for the slope coefficients on $\sigma_{i,\Delta DEF,t+1}$ and $\sigma_{i,\Delta TERM,t+1}$ are not uniformly positive and negative, respectively. Furthermore, also unlike Bali and Engle (2010), I do find that the slope coefficients on $\sigma_{i,\Delta FED,t+1}$ are highly significant.

Moreover, when looking at the risk premium induced by conditional covariation with climate transition shocks, Table 39 shows that the coefficients on $\sigma_{i,\epsilon^{CTI},t+1}$ are uniformly negative for all assets and returns with values ranging from -0.027 to -0.426. The slope coefficients on $\sigma_{i,\epsilon^{CTI},t+1}$ are significant at the 5% significance level when considering the individual stock returns, the long-term bond returns, and the portfolios sorted on size and investment. Additionally, with the 48 Industry Portfolios, the B_4 estimate with a p-value of 0.051 is significant at a 10% significance level. However, the coefficients are insignificant for the portfolios sorted on momentum and those sorted on size and book-to-market. Overall this indicates that when controlling for macroeconomic factors, climate transition risks are priced but not consistently.

	$\sigma_{im,t+1}$	$\sigma_{i,SMB,t+1}$	$\sigma_{i,HML,t+1}$	$\sigma_{i,RMW,t+1}$
Individual Stocks	8.334 (0.000)	1.851 (0.000)	2.009 (0.000)	2.497 (0.000)
Long-Term Bonds	5.456 (0.000)	3.306 (0.000)	5.967 (0.000)	0.890 (0.000)
48 Industry Portfolios	1.900 (0.000)	3.134 (0.000)	1.973 (0.000)	2.854 (0.000)
Size/Investment Sorted	3.313 (0.000)	1.472 (0.000)	0.557 (0.057)	1.132 (0.000)
Momentum Sorted	1.336 (0.056)	0.421 (0.255)	0.134 (0.803)	-0.055 (0.916)
Size/B-M Sorted	4.032 (0.000)	1.419 (0.000)	1.059 (0.002)	0.976 (0.000)

Table 40: Risk premia induced by conditional covariation with financial factors

	$\sigma_{i,CMA,t+1}$	$\sigma_{i,MOM,t+1}$	$\sigma_{i,\epsilon^{CTI},t+1}$
Individual Stocks	4.542 (0.000)	1.410 (0.000)	-0.404 (0.000)
Long-Term Bonds	-0.191 (0.435)	0.521 (0.027)	-1.228 (0.000)
48 Industry Portfolios	-0.339 (0.504)	1.254 (0.006)	-0.901 (0.072)
Size/Investment Sorted	-0.143 (0.600)	-0.4712 (0.067)	-0.032 (0.899)
Momentum Sorted	0.312 (0.579)	-0.420 (0.209)	-0.827 (0.066)
Size/B-M Sorted	-0.790 (0.006)	-0.389 (0.115)	-0.603 (0.018)

Table 41: Risk premia induced by conditional covariation with financial factors

Finally, Tables 40 and 41 show the estimates for the risk premia induced by conditional covariation with financial factors in addition to the climate transition factor. Similarly to what

Bali and Engle (2010) report, I find that the estimated coefficient for A is again highly significant when controlling for financial factors. However, I find a larger spread in estimates for A than before with values ranging from 1.336 to 8.334. Furthermore, like Bali and Engle (2010), I find that the coefficient on the conditional covariation with the HML factor is positive in all cases and statistically significant for most assets and portfolios. However, I also find that the coefficient on the conditional covariation with the SMB factor is always positive and, for most returns, significant, which contrasts with findings by Bali and Engle (2010). Furthermore, like Bali and Engle (2010), I also find that the coefficient on the conditional covariation with the Momentum factor is not consistently priced in the ICAPM framework.

Furthermore, when looking at the risk premium induced by conditional covariation with climate transition shocks when controlling for financial factors, Table 41 shows that the coefficients on $\sigma_{i,\epsilon^{CTI},t+1}$ are again uniformly negative for all assets and returns with values ranging from -0.032 to -1.228. The slope coefficients on $\sigma_{i,\epsilon^{CTI},t+1}$ are significant at the 5% significance level when considering the individual stock returns, the long-term bond returns, and the portfolios sorted on size and book-to-market. Additionally, the coefficients on the conditional covariation with climate transition shocks are significant at the 10%-significance level when considering the 48 Industry Portfolio and the momentum-sorted portfolios. However, the coefficients are insignificant for the portfolios sorted on size and investment. This indicates that climate transition risks are again priced but not consistently when controlling for financial factors.

4.5 Climate Transition Risk Premium Via Factor Mimicking Portfolios

As a final test to confirm the existence of a climate transition risk premium, I use Factor Mimicking Portfolios similar to Brogaard and Detzel (2015). This approach makes use of the fact that ICAPM implies linear pricing kernel models, as noted in Equations (12) and (13). Next, consider the projection $b'r_t^e$ of the pricing kernel m_t onto the space of excess returns r_t^e as shown in Equation (28) and Equation (29).

$$m_t = b'r_t^e + \epsilon_t \tag{28}$$

$$E(\epsilon_t r_t^e) = 0 \tag{29}$$

Then following Brogaard and Detzel (2015), Equations (13), (28), and (29) can be used to obtain the expression given in Equation (30).

$$0 = E(m_t r_t^e) = E((b'r_t^e + \epsilon_t)r_t^e) = E((b'r_t^e)r_t^e) \tag{30}$$

This is referred to as the factor-mimicking portfolio of m, which is a regression of the discount factor on excess returns. As Brogaard and Detzel (2015) note, $b'r_t^e$ also contains all relevant asset pricing information as m_t, but does not include the uninformative term ϵ_t that may include measurement error orthogonal to asset returns. This property, in turn, makes it convenient for empirical work to use factor-mimicking portfolios. Next, following Brogaard and Detzel (2015), I create factor mimicking portfolios for the climate transition factor as shown in Equation (31).

$$\epsilon_t^{CTI} = a + b'r_t^e + \eta_t \tag{31}$$

In Equation (31), ϵ_t^{CTI} represent the climate transition shocks recovered from Equation (19), and r_t^e are the returns on a set of basis assets, for which I, following Brogaard and Detzel (2015), choose the Fama French 25 size and Momentum Portfolios. Brogaard and Detzel (2015) selected these returns due to their sizeable spread in returns, which cannot be solely explained by a limited number of factors. Next, by using the estimated b' from Equation (31), I find the factor mimicking portfolio defined by Equation (32).

$$F_{CTI} = b' r_t^e \tag{32}$$

I subsequently make use of Fama-MacBeth regressions (Fama and MacBeth, 1973) to investigate whether the climate transition index factor-mimicking portfolio F_{CTI} is a factor that helps price assets. As Faccini et al. (2021) note, while Fama-MacBeth regressions can only take linear effects into account, they have the advantage over portfolio sorts that they are able to accommodate multiple regressors. In these regressions, I choose the Fama-French 48 industry portfolios since, as Faccini et al. (2021) and Graff Zivin and Neidell (2014) note, it is highly probable that the impact of climate risks varies greatly among different industries.

For these Fama-MacBeth regressions, I again use different sets of controls, namely, the tree factors by Fama and French (1993), the five factors by Fama and French (2015), the five factors augmented by the momentum factor by Carhart (1997). Consequently, I estimate Equation (33) for the final case.

$$\begin{aligned} r_{i,t}^e = \lambda_0 &+ \lambda_{MKT} \cdot \beta_{MKT}^i + \lambda_{HML} \cdot \beta_{HML}^i + \lambda_{SMB} \cdot \beta_{SMB}^i \\ &+ \lambda_{RMW} \cdot \beta_{RMW}^i + \lambda_{CMA} \cdot \beta_{CMA}^i + \lambda_{MOM} \cdot \beta_{MOM}^i + \lambda_{F_{CTI}} \cdot \beta_{F_{CTI}}^i \end{aligned} \tag{33}$$

Here, in the first step, for each industry portfolio, I estimate the beta coefficients for the various factors, including the factor-mimicking portfolio F_{CTI}. In the second step, I estimate the risk premia associated with each factor via cross-sectional regressions of the excess returns on the estimated beta coefficients obtained in the first step of the estimation procedure.

	CAPM	3 Factors	5 Factors	5 Factors + Mom
$\lambda_{F_{CTI}}$	-11.795 (0.000)	-7.851 (0.000)	-2.733 (0.000)	-2.535 (0.000)
λ_{MKT}	-1.785 (0.002)	3.896 (0.000)	8.024 (0.014)	4.9717 (0.000)
λ_{SMB}		-4.814 (0.070)	10.023 (0.004)	0.050 (0.984)
λ_{HML}		-0.577 (0.803)	-6.595 (0.039)	-0.699 (0.749)
λ_{RMW}			8.921 (0.018)	6.974 (0.007)
λ_{CMA}			9.548 (0.000)	20.758 (0.000)
λ_{MOM}				-54.005 (0.000)

Table 42: Risk premia Estimates

Table 42 shows that F_{CTI} carries a statistically significant negative risk premium when controlling for different factors. This again supports the existence of a climate transition risk premium that is found in previous sections of this thesis. However, it should be noted that the results reported in this section are only specific to a certain choice for the basis assets and test assets. It remains open to other researchers if the results obtained here are robust when other basis and test asset choices are made.

4.6 Conclusion Climate Transition Risk Premium

Overall, I find evidence for the existence of a statistically significant climate transition risk premium in both equity and long-term and short-term bond markets. This risk premium appears to have emerged in recent years, with no evidence of a significant risk premium before 2012. Instead, this risk premium appears to be driven by the period between 2012 and 2022. This conclusion generally stays the same when instead of using a multi-paper index, the climate transition shocks corresponding to the various papers that make up this index are individually examined. Additionally, by making use of the method by Bali and Engle (2010) that makes use of the Dynamic Conditional Correlation by Engle (2002) and by using factor-mimicking portfolios and Fama-MacBeth regressions as is done by Brogaard and Detzel (2015), I find further evidence for the existence of a climate transition risk premium. This risk premium associated with climate transition risks is further supported by my Climate Transition Index, which has predictive power for future excess stock and bond market returns. The existence of a climate transition risk premium has far-reaching consequences for financial institutions such as banks and insurance companies. Firstly, it shows the need to develop suitable risk management tools and strategies to obtain the desired exposure level to the climate transition's financial consequences. Secondly, it shows the need to properly prepare for the likely further incorporation of climate transition risks in stress tests and ORSAs, as will likely be mandated by regulators such as the DNB and ECB when the existence of such a risk premium is further accepted.

5 Quantile-on-Quantile Analysis

5.1 Introduction

With the previous section providing evidence for the existence of a recently emerged climate transition risk premium, the next obvious research area is to investigate how climate transition risks affect different assets. This is critical for financial institutions such as banks and insurance companies. Assets related to high-carbon industries may decline in value due to potential carbon pricing or regulatory changes. Conversely, assets in low-carbon or climate-resilient sectors may experience an increase in value as market preferences shift. For these financial institutions to be able to conduct risk management adequately, there is a need to gain a better understanding of how climate transition risks affect different industries and different commodity types.

I set out to investigate this research question by using the quantile-on-quantile (QQ) approach by Sim and Zhou (2015). This method combines quantile regression with non-parametric local linear regression. I carry this approach originally developed to investigate the effect of oil price shocks on stock markets over to investigate the effect of climate transition shocks. The QQ approach by Sim and Zhou (2015) can reveal hidden features in the relationship between returns and climate transition shocks that can remain unnoticed when using conventional methods like OLS or quantile regression. It does this by making the effects of these shocks dependent on both the prevailing market conditions and the sign and magnitude of climate transition shocks.

I begin this investigation by giving an overview of the quantile-on-quantile approach by Sim and Zhou (2015). Authors such as Ullah et al. (2023) have previously used this approach to study the impact of economic policy uncertainty on stock market returns. Subsequently, I show and discuss the results obtained for different commodity types, industry return series, and green investment funds. Finally, I also investigate the QQ approach's methodical validity in the context of this thesis.

5.2 Methodology

This section outlines the model formulated by Sim and Zhou (2015) applied to climate transition shocks instead of oil price shocks. The quantile-on-quantile approach has the ability to relate the quantile of returns with quantiles of climate transition shocks. Let θ denote a quantile of returns. The QQ approach starts by postulating the quantile of returns r_t as a function of shocks to the climate transition index, as shown in Equation (34).

$$r_t = \beta^{\theta}(CTI_t) + \nu_t^{\theta} \tag{34}$$

In Equation (34), CTI_t refers to the shocks to the climate transition index, ϵ_t^{CTI}, recovered from Equation (19). These shocks are renamed in this section to CTI_t for convenience. Furthermore, ν_t^{θ} is an error term with a zero θ-quantile, and $\beta^{\theta}()$ is a link function that is allowed to be unknown. Following Sim and Zhou (2015), I do this to not impose a prior on how climate transition risks and returns are related.

The QQ approach by Sim and Zhou (2015) continues by investigating Equation (34) in the neighborhood of CTI^{τ}, where CTI^{τ} denotes the τ-quantile of climate transition shocks. This is done to study the relationship between the θ-quantile of returns and the τ-quantile of climate transition shocks. As $\beta^{\theta}()$ is allowed to be unknown, this function is first linearized by taking a first-order Taylor expansion of $\beta^{\theta}()$ around CTI^{τ}. This then leads to the expression given in Equation (35).

$$\beta^{\theta}(CTI_t) \approx \beta^{\theta}(CTI^{\tau}) + \beta^{\theta'}(CTI^{\tau})(CTI_t - CTI^{\tau}) \tag{35}$$

In Equation (35), $\beta^{\theta}(CTI^{\tau})$ and $\beta^{\theta'}(CTI^{\tau})$ are both indexed in θ and τ. Note that the τ-quantile of climate transition shocks, CTI^{τ}, is only a function of τ. Next, considering that $\beta^{\theta}(CTI^{\tau})$ and $\beta^{\theta'}(CTI^{\tau})$ are both functions of θ and this CTI^{τ}, it, in turn, means that $\beta^{\theta}(CTI^{\tau})$ and $\beta^{\theta'}(CTI^{\tau})$ are functions of both θ and τ. Consequently, it is possible to rewrite $\beta^{\theta}(CTI^{\tau})$ as $\beta_0(\theta,\tau)$ and $\beta^{\theta'}(CTI^{\tau})$ as $\beta_1(\theta,\tau)$. Subsequently, Equation (35) can be rewritten as Equation (36) shown below.

$$\beta^{\theta}(CTI_t) \approx \beta_0(\theta,\tau) + \beta_1(\theta,\tau)(CTI_t - CTI^{\tau}) \tag{36}$$

Furthermore, substituting Equation (36) into Equation (34) results in Equation (37).

$$r_t = \underbrace{\beta_0(\theta,\tau) + \beta_1(\theta,\tau)(CTI_t - CTI^{\tau})}_{*} + \nu_t^{\theta} \tag{37}$$

In Equation (37), the expression given by $*$ is the conditional quantile of returns that can capture the overall relationship between returns and climate transition shocks by examining the dependence between their distributions, as β_0 and β_1 are both indexed by θ and τ.

Next, following Sim and Zhou (2015), Equation (37) is estimated to obtain estimates for $\beta_0(\theta,\tau)$ and $\beta_1(\theta,\tau)$ by solving the following expression given in Equation (38).

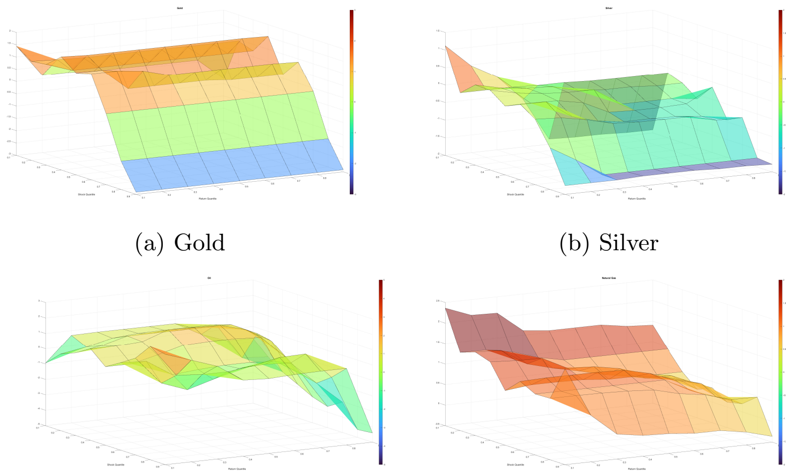
$$\underset{b_0,b_1}{min} \sum_{t=1}^{n} \rho_{\theta}[r_t - b_0 + b_1(C\hat{T}I_t - C\hat{T}I^{\tau})] K\left[\frac{F_n(CTI_t) - \tau}{h}\right] \tag{38}$$

In Equation (38), ρ_{θ} is the tilted absolute value function that gives the θ-conditional quantile of r_t as the solution, $C\hat{T}I_t$ is the estimated counterpart of CTI_t and $C\hat{T}I^{\tau}$ is the empirical quantile of CTI^{τ} . Furthermore, following Sim and Zhou (2015), as I am interested in the locally exerted effect of the τ-quantile of climate transition shocks, I make use of Gaussian Kernel $K[\cdot]$ in order to weigh the observations surrounding $C\hat{T}I^{\tau}$. Following Sim and Zhou (2015), I make the decision to use a plug-in bandwidth value for h equal to 0.05 in my estimations. It should be noted that, as is standard with kernel regressions, selecting an appropriate bandwidth parameter is one of the main challenges. The choice of bandwidth parameter involves a bias-variance trade-off. A larger bandwidth reduces variance by providing a smoother estimate but at the cost of increased bias. On the other hand, a smaller bandwidth reduces bias by capturing more local details, but at the expense of increased variance.

5.3 Results

In this section, I carry out the quantile-on-quantile approach by Sim and Zhou (2015) to investigate the effects of climate transition risk shocks depending on different financial conditions. I do this for a number of commodities, industry returns, and green investment funds. Of particular interest is to see the effect of the largest climate transition shocks, as this reveals what types of assets can become stranded assets in times of increased climate transition risks and which types of assets can serve as safe havens for climate transition risks. I begin by examining the effects of climate transition shocks on different commodity types.

5.3.1 Commodities



(a) Gold (b) Silver

(c) Oil (d) Natural Gas

Figure 6: Commodities QQR Slope Estimates

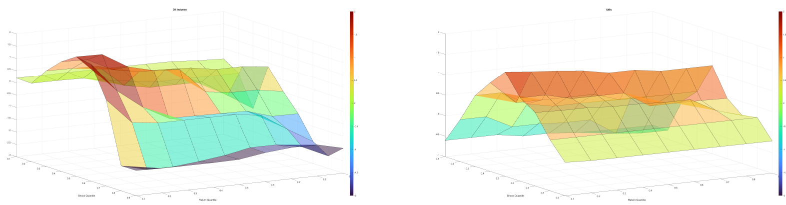
Figure 6 shows the estimates for $\beta_1(\theta, \tau)$ when considering the returns on several different commodity types. These are gold, silver, oil, and natural gas. These figures show that the most extreme positive climate transition shocks have a large negative effect on gold and silver returns for all market conditions. Also, the largest negative climate transition shocks have a negative effect on silver returns, but only during periods when silver returns were already high. This would suggest that gold and silver cannot serve as safe havens against severe climate transition risks in the same way that they can function as safe havens from uncertainty from economic policy innovation or geopolitical risk, as Chiang (2022) found.

Furthermore, Figure 6 also reveals that for all oil market conditions, but especially for the largest quantile of oil returns, the largest climate transition shocks are associated with increased oil returns. This may be uncertainty regarding the long-term sustainability of oil assets, increasing borrowing costs, and limiting access to capital for companies in the oil industry. This can, for example, lead to cuts in production that create short-term supply constraints and subsequently cause short-term price increases. Furthermore, for natural gas, extreme positive climate transition shocks are only associated with higher returns when the returns on natural gas are already low. For the other market conditions, large climate transition shocks are associated with lower returns on natural gas. Furthermore, for all quantiles of natural gas returns, but especially when returns on natural gas are already low, large negative climate transition shocks are associated with increased returns on natural gas.

5.3.2 Industry Returns

This section continues by examining the effects of climate transition shocks on the return of different industry sectors.

5.3.2.1 Energy and Resources



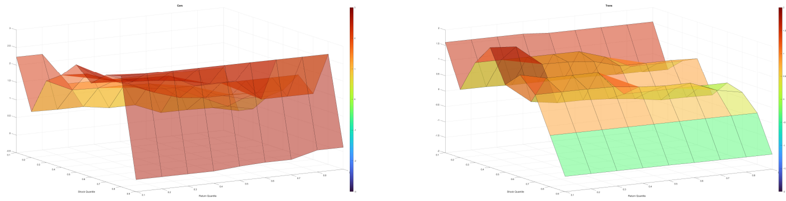
(a) Oil Industry (b) Utilities

Figure 7: Energy and Resources QQR Slope Estimates

Figure 7 shows the estimates for $\beta_1(\theta, \tau)$ for firms related to oil and petroleum products and the estimates for utility companies. First, when looking at the effect on firms in the oil industry, it is noticeable that for all market conditions, large positive climate transition shocks are associated with a decrease in returns for all prevailing market conditions. However, this effect is slightly more pronounced at the lower quantiles of oil industry returns. A possible explanation is that large climate transition shocks signal the introduction of extensive climate legislation that, for example, has the goal of phasing out the usage of fossil fuels rendering many investments of these companies obsolete and reducing the long-term profitability of such companies due to stranded assets.

Furthermore, for utility companies, both large positive and negative climate transition shocks are associated with lower returns. A possible explanation might be that these return series include both utility companies that have already invested significantly in renewable energy sources and companies that have not. During times of large negative climate transition shocks, utility companies that had already been starting to transition towards cleaner energy sources may face increased competition from cheaper fossil fuel alternatives. This can negatively impact their market share and profitability, particularly if they have made significant investments in renewable energy that are now less economically viable. At the same time, large positive climate transition shocks can render investments by utility companies with major fossil investments obsolete, reducing their profitability.

5.3.2.2 Automotive and Transportation



(a) Automobiles (b) Transportation

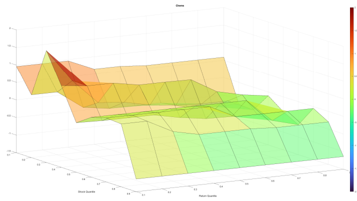
Figure 8: Automotive and Transportation QQR Slope Estimates

Figure 8 shows how different quantiles of climate transition shocks affect the return of companies in the automotive and transportation industries. When looking at the effects of climate transition shocks on returns of the automobile sector, it is noticeable that the estimates for $\beta_1(\theta, \tau)$ are positive for most quantiles of returns and almost all quantiles of returns. Only for the largest positive climate transition shocks does this relationship not hold, especially for the lower quantiles of returns where the effect is negative. This can be explained by these large positive shocks signaling stricter emissions standards for vehicles leading to increased production costs that reduce the profit margins for automobile manufacturers.

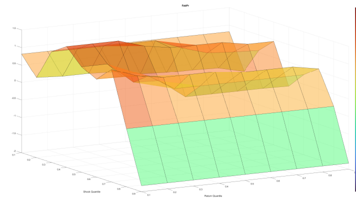
Furthermore, Figure 8 shows that extreme negative climate transition shocks indicating sudden decreased climate legislative pressure are associated with increased returns for companies in the transportation sector. In contrast, large positive climate transition shocks are associated with decreased returns for all prevailing market conditions. This can be caused by transportation companies being required to reduce their carbon footprint by adopting cleaner technologies, such as electric or hybrid vehicles, or by improving fuel efficiency. This can mean that significant investments are needed by such companies in order to be able to continue operating, which can significantly reduce the profitability of such companies.

5.3.2.3 Manufacturing, Industrial, and Construction

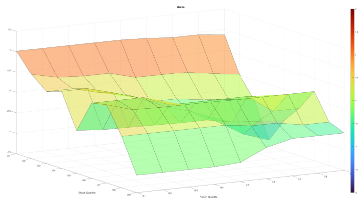
Figure 9 shows the estimates for $\beta_1(\theta, \tau)$ for the returns of manufacturing, industrial, and construction industry portfolios. Generally, negative climate transition shocks are associated with increased returns, and positive climate shocks are associated with decreased returns for these portfolios for all market conditions. For these industries, increased climate legislation often requires companies to adopt new technologies, processes, and practices to reduce their environmental impact, which can decrease profitability. A noticeable exception, however, is mining and mineral companies. Large positive climate transition shocks for these mining companies are only associated with lower returns with higher quantiles of returns. Instead, when the returns of these firms are already high, large positive climate shocks are actually associated with higher returns.



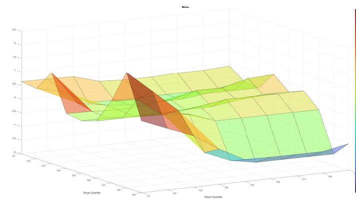
(a) Chemicals



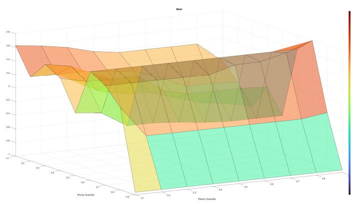
(b) Fabricated Products



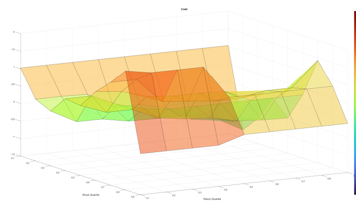
(c) Machinery and Business Equipment



(d) Mining and Minerals



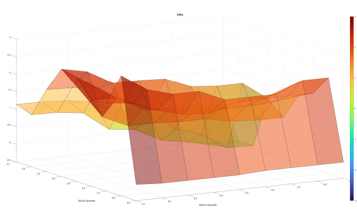
(e) Steel



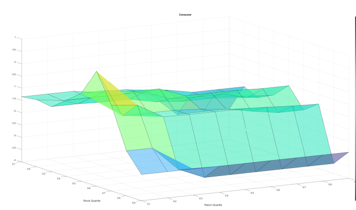
(f) Construction

Figure 9: Manufacturing, Industrial, and Construction QQR Slope Estimates

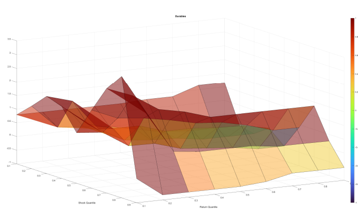
5.3.2.4 Consumer Goods and Retail



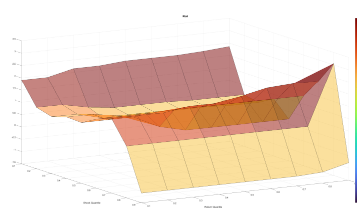
(a) Clothing



(b) Consumer Products



(c) Consumer Durables

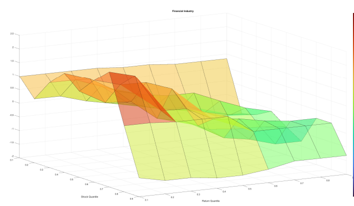


(d) Retail Stores

Figure 10: Consumer Goods and Retail QQR Slope Estimates

Figure 10 shows how different climate transition shocks affect the returns of different portfolios of companies associated with consumer goods or retail stores. Noticeably, for all market conditions for the different portfolios, $\beta_1(\theta, \tau)$ associated with the largest quantile of climate transition shocks are negative. This indicates that increased climate legislation is associated with decreased returns for these portfolios, and these types of companies are thus not safeguarded from the effects of tightening climate legislation. A possible explanation might be that such companies may be forced to adjust their supply chain practices substantially. Such changes can introduce disruptions, lead to delays, and incur additional costs, ultimately impacting profitability and returns for these companies.

5.3.2.5 Financial and Insurance

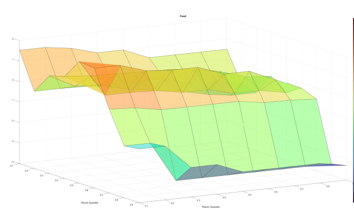


(a) Financial and Insurance

Figure 11: Financial and Insurance QQR Slope Estimates

Next, Figure 11 shows how the returns of a portfolio of financial and insurance companies react to different sizes of shocks at various market conditions. This figure shows that large negative climate transition shocks at all market conditions are associated with increased returns and large positive shocks are associated with decreased returns. A possible explanation might be that financial companies can be exposed both via decreased returns on their investment portfolios due to lower returns of other types of firms or by financial institutions themselves facing stricter regulations and reporting requirements, which can impact profitability and lower returns.

5.3.2.6 Food and Agriculture

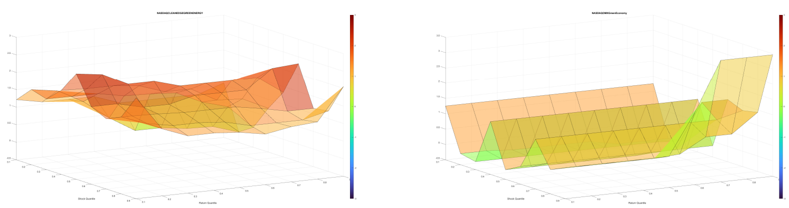


(a) Food and Agriculture

Figure 12: Food and Agriculture QQR Slope Estimates

Next, Figure 12 shows how different climate transition shocks affect the returns of a portfolio of food and agriculture companies at various market conditions. It is again noticeable how large negative shocks at all market conditions are associated with increased returns, and large positive shocks are associated with lower returns. This may be explained by increased climate legislation requiring food and agricultural companies to invest in more sustainable and environmentally friendly farming practices that can lead to additional costs due to reducing greenhouse gas emissions or using organic fertilizers instead of conventional methods being more expensive. This can squeeze profit margins and reduce returns.

5.3.3 Green Investment Fund



(a) NASDAQ CLEAN EDGE GREEN ENERGY (b) NASDAQ OMX Green Economy

Figure 13: Green Investment QQR Slope Estimates

Finally, Figure 13 shows the estimates for $\beta_1(\theta, \tau)$ for the returns for two different green investment funds, namely the NASDAQ Clean Edge Green Energy Index, which tracks the performance of clean energy technology companies, and the NASDAQ OMX Green Economy Index which tracks the performance of companies associated with the economic framework of sustainable development across various sectors of the economy. Unlike many of the previous industry returns, large positive climate transition shocks are actually associated with increased returns for these investment vehicles. Increases in legislation on climate change can mean growing market opportunities for companies involved in clean energy technology leading to increased returns. Additionally, increased climate legislation may also positively affect the competitive position of companies that have invested more in sustainability compared to their competitors leading to increased returns. Overall, this finding of the good performance of green investment funds is consistent with the finding of Cepni et al. (2022), who discover that green assets can offer reliable, safe-haven benefits against climate uncertainty.

5.3.4 Conclusion

The quantile-on-quantile approach reveals that sudden large increases in climate transition risks are not limited to negatively impacting firms commonly believed to be heavily affected by climate legislation, such as energy and resources companies, automotive and transportation companies, and manufacturing and industrial companies. Instead, financial institutions and consumer and retail companies also see decreased returns during times of substantial climate legislative pressure. This has considerable consequences for risk management as investing in a diversified portfolio of different industries does not mean that exposure to climate transition risks is automatically diversified away. Also, traditional safe-haven assets such as gold or silver are not suited for protecting against climate transition risks. However, green investment funds do seem to react positively to climate transition shocks, confirming findings by Cepni et al. (2022).

5.4 Robustness Analysis

As a final step, I conclude this section by checking the validity of the quantile-on-quantile approach. As Sim and Zhou (2015) state, the principle behind the QQ approach is to decompose the quantile regression estimates so that they are specific to the different quantiles of explanatory variables. Consequently, the quantile-on-quantile approach should be able to express more information regarding the relationship between the variables of interest due to the quantile-on-quantile approach allowing for this relationship to be heterogeneous across τ.

If the quantile-on-quantile approach is indeed able to decompose the quantile regression estimates, then it should be possible to use the QQ estimates to recover the quantile regression estimates. Since the quantile regression estimates are only indexed by θ, it should then be possible to construct estimates from the quantile-on-quantile regression estimates, $\bar{\beta}_1(\theta)$, that are also only indexed by θ by averaging over τ as is shown in Equation (39), where $\hat{\beta}_1(\theta, \tau)$ represent the obtained estimates for $\beta_1(\theta, \tau)$.

$$\bar{\beta}_1(\theta) = \frac{1}{S} \sum_{\tau} \hat{\beta}_1(\theta, \tau) \tag{39}$$

To facilitate this test, I also estimate the regular quantile regression for all the different return series by estimating Equation (40).

$$\hat{r}_t^{\theta} = \hat{\gamma}_0(\theta) + \hat{\gamma}_1(\theta) \cdot CTI_t \tag{40}$$

Figures A6 until A13 show for the various returns considered, the averaged over τ quantile-on-quantile approach regression estimates, $\bar{\beta}_1(\theta)$ in green. Furthermore, the quantile regression estimates for $\gamma_1(\theta)$ are shown in red for all the different returns considered, as these figures show that the averaged over τ quantile-on-quantile estimates seem to follow the quantile regression generally. This simple visual manner confirms the validity of the results obtained in the previous section.

6 Conclusion & Discussion

Overall, the findings of this thesis emphasize the importance of taking the effects of the transition to a more sustainable economy into account. First, this thesis contributes to existing literature relating to the effects of climate change on financial markets by constructing a novel index of climate transition risks using deep-learning techniques. I subsequently use this index to provide evidence for a statistically significant climate transition risk premium in U.S. equity markets and long-term and short-term bond markets arising in recent years. This finding related to climate transition risks is consistent with the general intertemporal hedging hypothesis by Merton (1973), where investors accept reduced returns on assets that serve as effective hedges against unfavorable changes in the investment opportunity set. Furthermore, I find evidence for this index having a negative contemporaneous correlation between changes in my climate transition index, excess stock market returns, excess bond market returns, and macroeconomic activity. Additionally, I find that the climate transition index has predictive power on future excess stock and bond market returns, suggesting further that climate transition risks have asset pricing implications.

This existence of a climate transition risk premium has far-reaching consequences for financial institutions such as banks and insurance companies. First, it shows the need to develop suitable risk management tools and strategies to obtain the desired exposure to the climate transition's financial consequences. Secondly, it shows the need to properly prepare for the likely further incorporation of climate transition risks in stress tests and ORSAs, as will likely be mandated by regulators such as the DNB and ECB when the existence of such a risk premium is further accepted.

Moreover, to conduct a more comprehensive analysis of the impact of climate transition risks on various industry portfolios' return series that can contribute to better risk management by financial institutions, I employ the quantile-on-quantile (QQ) methodology developed by Sim and Zhou (2015). This approach unveils that not only sectors traditionally associated with suffering from climate transition risks, like the oil and petroleum industry, but also companies operating in the manufacturing and consumer goods sectors experience diminished returns during periods of heightened climate transition risks. These findings hold significant implications for risk management strategies that financial institutions such as banks and insurance companies employ. Additionally, this study discovers evidence indicating that green investment funds demonstrate increased returns during periods of extreme climate transition risks, suggesting their potential role as hedges or safe havens against such risks. This finding further emphasizes the relevance and potential value of these assets in navigating the challenges posed by climate transition.

Finally, I will end this thesis with a discussion of some of the shortcomings of this thesis and recommendations for future research. It should be noted that in the investigation into the existence of a climate transition risk premium via portfolio sorts, a particular choice is made for the length of the rolling window. Furthermore, also in the quantile-on-quantile, a particular choice for the bandwidth parameter is made. These choices are not further investigated, and it remains an open question whether similar results are obtained when different choices are made. As a final note, this thesis has also only made use of U.S. newspapers in the construction of the index and of U.S. financial markets. It thus remains open to see whether the results I obtained are also seen in different economies and if there are potential cross-country effects.

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Appendices

Model Architecture & Performance

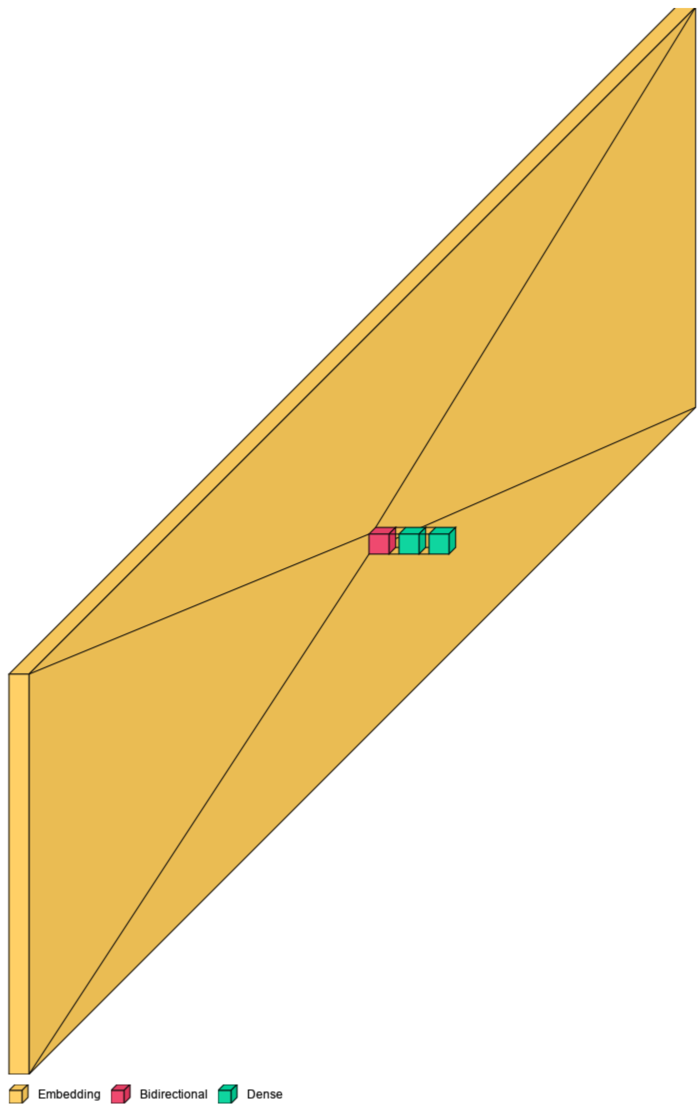


Figure A1: BiLSTM Architecture.

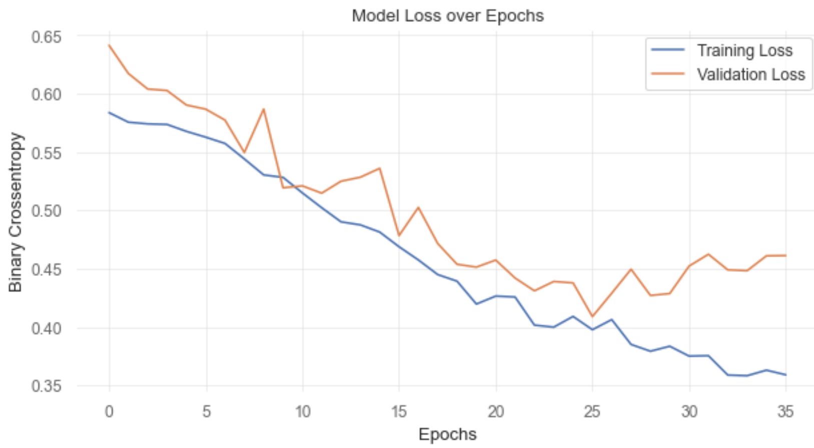


Figure A2: Model Loss.

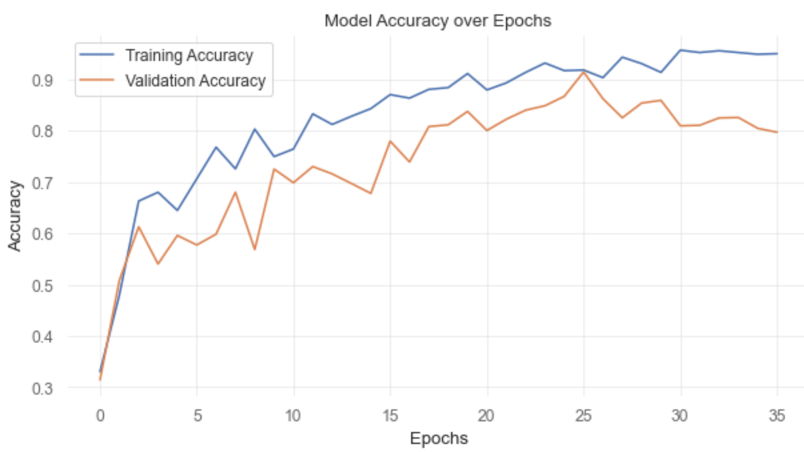


Figure A3: Model Accuracy.

Macroeconomic Activity

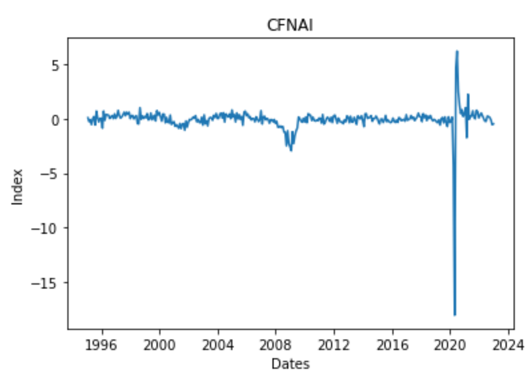


Figure A4: CFNAI

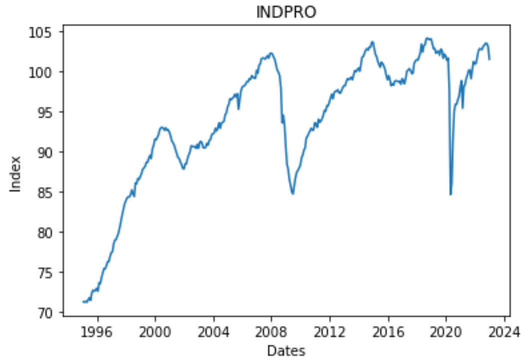


Figure A5: Industrial Production Index

Climate Transition Risk Premium Via Portfolio Sorts using Individual Newspapers

Equities

WSJ

Alpha	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	0.277 (0.118)	0.210 (0.100)	0.128 (0.287)	0.195 (0.100)
Second	0.089 (0.577)	0.033 (0.779)	-0.086 (0.414)	-0.026 (0.788)
Third	-0.068 (0.640)	-0.117 (0.265)	-0.276 (0.002)	-0.224 (0.007)
Fourth	0.003 (0.984)	-0.053 (0.626)	-0.226 (0.024)	-0.166 (0.066)
Fifth	0.170 (0.322)	0.104 (0.449)	0.013 (0.926)	0.087 (0.509)
Spread	-0.107 (0.393)	-0.106 (0.392)	-0.115 (0.382)	-0.108 (0.412)

Table 43: Alpha Estimates 1995-2022

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	-0.250 (0.251)	-0.170 (0.288)	-0.159 (0.306)	-0.099 (0.518)
SECOND	-0.184 (0.349)	-0.149 (0.307)	-0.164 (0.243)	-0.122 (0.388)
THIRD	-0.334 (0.038)	-0.309 (0.011)	-0.322 (0.006)	-0.303 (0.013)
FOURTH	-0.311 (0.042)	-0.263 (0.007)	-0.270 (0.005)	-0.232 (0.021)
FIFTH	-0.325 (0.091)	-0.235 (0.072)	-0.251 (0.063)	-0.218 (0.115)
SPREAD	-0.075 (0.711)	-0.066 (0.755)	-0.092 (0.669)	-0.119 (0.581)

Table 44: Alpha Estimates 1995-2012

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	0.693 (0.004)	0.515 (0.003)	0.367 (0.031)	0.414 (0.009)
SECOND	0.323 (0.166)	0.184 (0.302)	0.011 (0.948)	0.053 (0.710)
THIRD	0.067 (0.750)	-0.049 (0.732)	-0.275 (0.027)	-0.237 (0.027)
FOURTH	0.080 (0.721)	-0.042 (0.768)	-0.290 (0.035)	-0.249 (0.036)
FIFTH	0.418 (0.083)	0.275 (0.174)	0.109 (0.594)	0.160 (0.401)
SPREAD	-0.275 (0.084)	-0.240 (0.126)	-0.258 (0.135)	-0.254 (0.142)

Table 45: Alpha Estimates 2012-2022

NYT

Alpha	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	0.230 (0.221)	0.165 (0.272)	0.055 (0.687)	0.133 (0.289)
Second	0.070 (0.656)	0.012 (0.914)	-0.126 (0.215)	-0.073 (0.440)
Third	0.007 (0.962)	-0.044 (0.696)	-0.189 (0.067)	-0.143 (0.163)
Fourth	0.030 (0.847)	-0.024 (0.835)	-0.191 (0.054)	-0.136 (0.147)
Fifth	0.134 (0.456)	0.070 (0.610)	0.004 (0.979)	0.085 (0.540)
Spread	-0.097 (0.542)	-0.096 (0.545)	-0.052 (0.745)	-0.048 (0.766)

Table 46: Alpha Estimates 1995-2022

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	-0.337 (0.057)	-0.234 (0.149)	-0.253 (0.108)	-0.183 (0.256)
Second	-0.251 (0.107)	-0.211 (0.062)	-0.207 (0.067)	-0.164 (0.152)
Third	-0.303 (0.078)	-0.268 (0.023)	-0.267 (0.016)	-0.237 (0.044)
Fourth	-0.202 (0.274)	-0.174 (0.137)	-0.186 (0.087)	-0.175 (0.108)
Fifth	-0.311 (0.216)	-0.240 (0.139)	-0.252 (0.100)	-0.217 (0.191)
Spread	0.026 (0.920)	-0.006 (0.978)	0.001 (0.998)	-0.034 (0.888)

Table 47: Alpha Estimates 1995-2012

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	0.608 (0.022)	0.445 (0.019)	0.252 (0.175)	0.303 (0.065)
SECOND	0.256 (0.268)	0.119 (0.444)	-0.100 (0.510)	-0.064 (0.634)
THIRD	0.176 (0.416)	0.062 (0.709)	-0.165 (0.296)	-0.133 (0.370)
FOURTH	0.131 (0.556)	0.007 (0.969)	-0.229 (0.129)	-0.187 (0.182)
FIFTH	0.411 (0.103)	0.251 (0.223)	0.163 (0.430)	0.222 (0.244)
SPREAD	-0.197 (0.345)	-0.194 (0.335)	-0.089 (0.683)	-0.081 (0.713)

Table 48: Alpha Estimates 2012-2022

WP

Alpha	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	0.367 (0.057)	0.297 (0.038)	0.184 (0.173)	0.285 (0.019)
Second	0.057 (0.744)	-0.004 (0.973)	-0.169 (0.126)	-0.091 (0.327)
Third	0.053 (0.743)	-0.002 (0.983)	-0.172 (0.095)	-0.130 (0.201)
Fourth	-0.003 (0.981)	-0.057 (0.579)	-0.181 (0.048)	-0.135 (0.117)
Fifth	-0.001 (0.997)	-0.055 (0.683)	-0.109 (0.414)	-0.063 (0.642)
Spread	-0.367 (0.017)	-0.352 (0.015)	-0.294 (0.056)	-0.348 (0.021)

Table 49: Alpha Estimates 1995-2022

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
First	-0.294 (0.200)	-0.185 (0.255)	-0.202 (0.190)	-0.096 (0.570)
Second	-0.290 (0.079)	-0.248 (0.034)	-0.264 (0.023)	-0.228 (0.051)
Third	-0.218 (0.126)	-0.191 (0.044)	-0.204 (0.027)	-0.203 (0.028)
Fourth	-0.241 (0.124)	-0.210 (0.050)	-0.203 (0.054)	-0.185 (0.064)
Fifth	-0.361 (0.064)	-0.293 (0.032)	-0.293 (0.031)	-0.264 (0.061)
Spread	-0.066 (0.680)	-0.109 (0.528)	-0.091 (0.599)	-0.168 (0.362)

Table 50: Alpha Estimates 1995-2012

	CAPM	3 Factor	5 Factor	5 Factor + Momentum
FIRST	0.779 (0.003)	0.621 (0.001)	0.446 (0.018)	0.510 (0.002)
SECOND	0.266 (0.304)	0.124 (0.484)	-0.138 (0.387)	-0.082 (0.496)
THIRD	0.199 (0.408)	0.071 (0.651)	-0.187 (0.232)	-0.154 (0.300)
FOURTH	0.117 (0.561)	-0.011 (0.939)	-0.197 (0.149)	-0.163 (0.194)
FIFTH	0.221 (0.347)	0.079 (0.703)	-0.002 (0.992)	0.031 (0.879)
SPREAD	-0.557 (0.013)	-0.542 (0.007)	-0.448 (0.046)	-0.479 (0.030)

Table 51: Alpha Estimates 2012-2022

Short-Term Bonds

WSJ

	(1)	(2)	(3)
FIRST	-0.222 (0.744)	0.853 (0.284)	0.850 (0.339)
SECOND	-0.685 (0.305)	0.305 (0.711)	0.507 (0.583)
THIRD	-0.409 (0.522)	0.642 (0.388)	0.775 (0.360)
FOURTH	-0.542 (0.417)	0.463 (0.558)	0.555 (0.528)
FIFTH	-0.756 (0.234)	0.200 (0.772)	0.418 (0.594)
SPREAD	-0.534 (0.003)	-0.653 (0.001)	-0.433 (0.038)

Table 52: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	-0.073 (0.465)	0.153 (0.200)	0.165 (0.149)
SECOND	0.035 (0.675)	0.255 (0.003)	0.264 (0.003)
THIRD	-0.009 (0.900)	0.150 (0.137)	0.161 (0.109)
FOURTH	0.009 (0.900)	0.164 (0.018)	0.168 (0.014)
FIFTH	-0.030 (0.739)	0.102 (0.304)	0.109 (0.246)
SPREAD	0.052 (0.255)	-0.042 (0.618)	-0.047 (0.549)

Table 53: Alpha Estimates 2003-2012

	(1)	(2)	(3)
FIRST	0.231 (0.032)	0.382 (0.000)	0.382 (0.000)
SECOND	0.020 (0.646)	0.073 (0.102)	0.075 (0.095)
THIRD	-0.025 (0.315)	0.003 (0.900)	0.005 (0.845)
FOURTH	-0.070 (0.004)	-0.052 (0.040)	-0.050 (0.051)
FIFTH	-0.324 (0.000)	-0.296 (0.000)	-0.295 (0.000)
SPREAD	-0.555 (0.000)	-0.679 (0.000)	-0.677 (0.000)

Table 54: Alpha Estimates 2012-2022

NYT

	(1)	(2)	(3)
FIRST	-0.295 (0.646)	0.397 (0.555)	0.469 (0.494)
SECOND	-0.518 (0.382)	0.191 (0.755)	0.279 (0.661)
THIRD	-0.184 (0.749)	0.552 (0.386)	0.671 (0.301)
FOURTH	-0.608 (0.319)	0.326 (0.564)	0.423 (0.463)
FIFTH	-0.772 (0.182)	0.157 (0.776)	0.252 (0.651)
SPREAD	-0.457 (0.032)	-0.222 (0.503)	-0.192 (0.544)

Table 55: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	-0.218 (0.809)	1.118 (0.271)	1.190 (0.212)
SECOND	0.108 (0.880)	1.637 (0.018)	1.674 (0.014)
THIRD	-0.079 (0.911)	1.519 (0.133)	1.624 (0.106)
FOURTH	0.296 (0.729)	2.558 (0.003)	2.652 (0.003)
FIFTH	-0.719 (0.474)	1.544 (0.197)	1.653 (0.149)
SPREAD	-0.506 (0.268)	0.422 (0.620)	0.467 (0.550)

Table 56: Alpha Estimates 2003-2012

	(1)	(2)	(3)
FIRST	-0.222 (0.744)	0.853 (0.284)	0.850 (0.339)
SECOND	-0.685 (0.305)	0.305 (0.711)	0.507 (0.583)
THIRD	-0.409 (0.522)	0.642 (0.388)	0.775 (0.360)
FOURTH	-0.542 (0.417)	0.463 (0.558)	0.555 (0.528)
FIFTH	-0.756 (0.234)	0.200 (0.772)	0.418 (0.594)
SPREAD	-0.534 (0.003)	-0.653 (0.001)	-0.433 (0.038)

Table 57: Alpha Estimates 2012-2022

WP

	(1)	(2)	(3)
FIRST	-0.220 (0.730)	0.296 (0.641)	0.349 (0.586)
SECOND	-0.386 (0.502)	0.142 (0.805)	0.208 (0.722)
THIRD	-0.137 (0.824)	0.411 (0.529)	0.500 (0.447)
FOURTH	-0.452 (0.472)	0.243 (0.664)	0.315 (0.575)
FIFTH	-0.575 (0.306)	0.117 (0.834)	0.187 (0.733)
SPREAD	-0.340 (0.191)	-0.165 (0.590)	-0.143 (0.633)

Table 58: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	-0.152 (0.807)	0.780 (0.313)	0.830 (0.284)
SECOND	0.076 (0.885)	1.142 (0.037)	1.167 (0.034)
THIRD	-0.055 (0.916)	1.059 (0.179)	1.132 (0.159)
FOURTH	0.206 (0.699)	1.783 (0.009)	1.849 (0.007)
FIFTH	-0.501 (0.483)	1.077 (0.363)	1.152 (0.312)
SPREAD	-0.353 (0.363)	0.294 (0.675)	0.326 (0.606)

Table 59: Alpha Estimates 2003-2012

	(1)	(2)	(3)
FIRST	-0.165 (0.836)	0.635 (0.416)	0.633 (0.447)
SECOND	-0.510 (0.483)	0.227 (0.766)	0.378 (0.633)
THIRD	-0.304 (0.694)	0.478 (0.570)	0.577 (0.513)
FOURTH	-0.404 (0.605)	0.344 (0.639)	0.413 (0.599)
FIFTH	-0.563 (0.423)	0.149 (0.835)	0.311 (0.674)
SPREAD	-0.398 (0.154)	-0.486 (0.048)	-0.322 (0.116)

Table 60: Alpha Estimates 2012-2022

Long-Term Bonds

WSJ

	(1)	(2)	(3)
FIRST	0.074 (0.480)	0.242 (0.018)	0.244 (0.014)
SECOND	-0.020 (0.749)	0.078 (0.219)	0.085 (0.188)
THIRD	-0.036 (0.480)	0.040 (0.450)	0.048 (0.371)
FOURTH	-0.052 (0.282)	0.009 (0.856)	0.018 (0.717)
FIFTH	-0.179 (0.017)	-0.128 (0.084)	-0.118 (0.118)
SPREAD	-0.253 (0.000)	-0.370 (0.000)	-0.362 (0.000)

Table 61: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.039 (0.754)	0.424 (0.047)	0.427 (0.030)
SECOND	-0.034 (0.643)	0.196 (0.034)	0.202 (0.031)
THIRD	-0.033 (0.638)	0.153 (0.056)	0.159 (0.045)
FOURTH	-0.023 (0.773)	0.127 (0.171)	0.135 (0.123)
FIFTH	0.002 (0.991)	0.101 (0.572)	0.114 (0.491)
SPREAD	-0.037 (0.863)	-0.322 (0.294)	-0.312 (0.264)

Table 62: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.098 (0.436)	0.280 (0.018)	0.300 (0.029)
SECOND	-0.010 (0.883)	0.094 (0.271)	0.108 (0.264)
THIRD	-0.036 (0.532)	0.043 (0.562)	0.055 (0.504)
FOURTH	-0.065 (0.242)	0.003 (0.962)	0.016 (0.835)
FIFTH	-0.234 (0.003)	-0.135 (0.115)	-0.128 (0.198)
SPREAD	-0.332 (0.000)	-0.415 (0.000)	-0.427 (0.000)

Table 63: Alpha Estimates 2012-2022

NYT

	(1)	(2)	(3)
FIRST	0.049 (0.398)	0.162 (0.004)	0.163 (0.002)
SECOND	-0.013 (0.788)	0.052 (0.285)	0.056 (0.245)
THIRD	-0.024 (0.608)	0.027 (0.566)	0.032 (0.492)
FOURTH	-0.035 (0.459)	0.006 (0.897)	0.012 (0.794)
FIFTH	-0.119 (0.029)	-0.085 (0.117)	-0.079 (0.141)
SPREAD	-0.169 (0.000)	-0.247 (0.000)	-0.241 (0.000)

Table 64: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.026 (0.696)	0.282 (0.055)	0.285 (0.030)
SECOND	-0.023 (0.640)	0.131 (0.116)	0.134 (0.105)
THIRD	-0.022 (0.659)	0.102 (0.169)	0.106 (0.161)
FOURTH	-0.016 (0.784)	0.085 (0.266)	0.090 (0.246)
FIFTH	0.001 (0.990)	0.068 (0.548)	0.076 (0.487)
SPREAD	-0.025 (0.797)	-0.215 (0.131)	-0.208 (0.105)

Table 65: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.098 (0.436)	0.280 (0.018)	0.300 (0.029)
FIRST	0.066 (0.402)	0.187 (0.010)	0.200 (0.011)
SECOND	-0.007 (0.917)	0.063 (0.392)	0.072 (0.352)
THIRD	-0.024 (0.704)	0.029 (0.688)	0.037 (0.620)
FOURTH	-0.043 (0.503)	0.002 (0.975)	0.010 (0.885)
FIFTH	-0.156 (0.034)	-0.090 (0.210)	-0.085 (0.256)
SPREAD	-0.221 (0.000)	-0.277 (0.000)	-0.285 (0.000)

Table 66: Alpha Estimates 2003-2022

WP

	(1)	(2)	(3)
FIRST	0.093 (0.429)	0.303 (0.008)	0.305 (0.006)
SECOND	-0.024 (0.803)	0.097 (0.334)	0.106 (0.296)
THIRD	-0.045 (0.636)	0.050 (0.605)	0.060 (0.537)
FOURTH	-0.065 (0.497)	0.011 (0.907)	0.023 (0.815)
FIFTH	-0.224 (0.044)	-0.160 (0.153)	-0.148 (0.183)
SPREAD	-0.317 (0.000)	-0.463 (0.000)	-0.453 (0.000)

Table 67: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.048 (0.696)	0.529 (0.055)	0.533 (0.030)
SECOND	-0.043 (0.640)	0.245 (0.116)	0.252 (0.105)
THIRD	-0.042 (0.659)	0.191 (0.169)	0.199 (0.161)
FOURTH	-0.029 (0.784)	0.159 (0.266)	0.168 (0.246)
FIFTH	0.002 (0.990)	0.127 (0.548)	0.143 (0.487)
SPREAD	-0.046 (0.797)	-0.403 (0.131)	-0.391 (0.105)

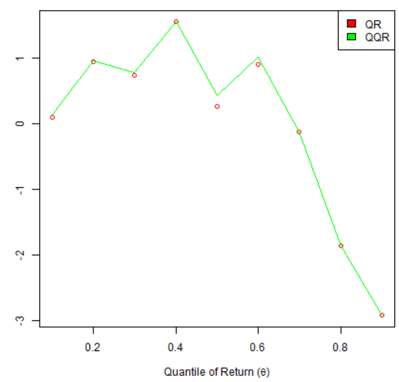
Table 68: Alpha Estimates 2003-2022

	(1)	(2)	(3)
FIRST	0.123 (0.402)	0.350 (0.010)	0.375 (0.011)
SECOND	-0.013 (0.917)	0.118 (0.392)	0.135 (0.352)
THIRD	-0.045 (0.704)	0.054 (0.688)	0.069 (0.620)
FOURTH	-0.081 (0.503)	0.004 (0.975)	0.020 (0.885)
FIFTH	-0.292 (0.034)	-0.169 (0.210)	-0.159 (0.256)
SPREAD	-0.415 (0.000)	-0.519 (0.000)	-0.534 (0.000)

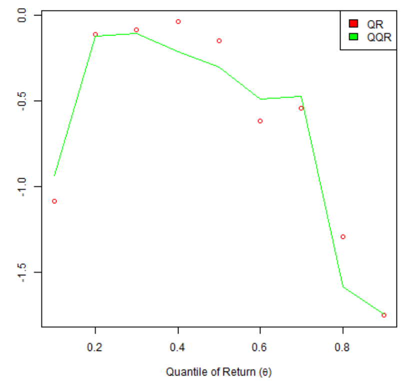
Table 69: Alpha Estimates 2003-2022

Robustness Analysis QQR

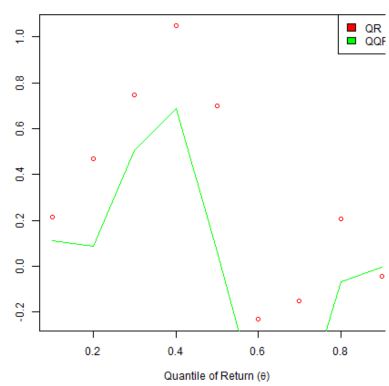
Commodities



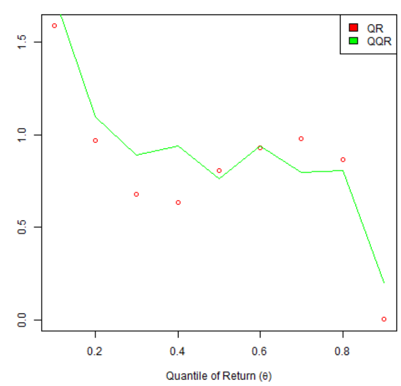
(a) Gold



(b) Silver



(c) Oil

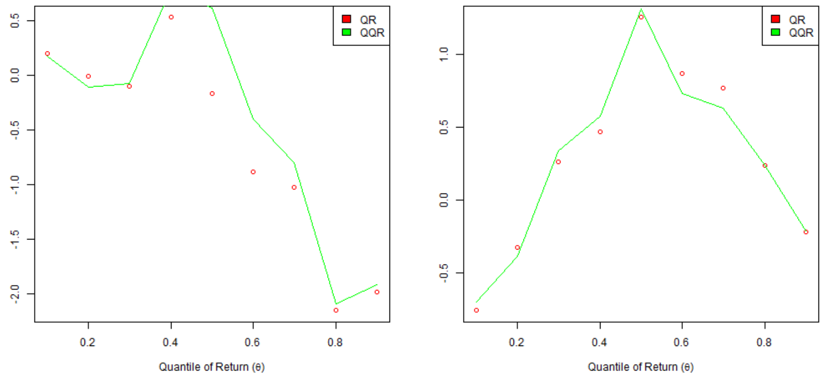


(d) Natural Gas

Figure A6: QR QQR Comparison

Industry Returns

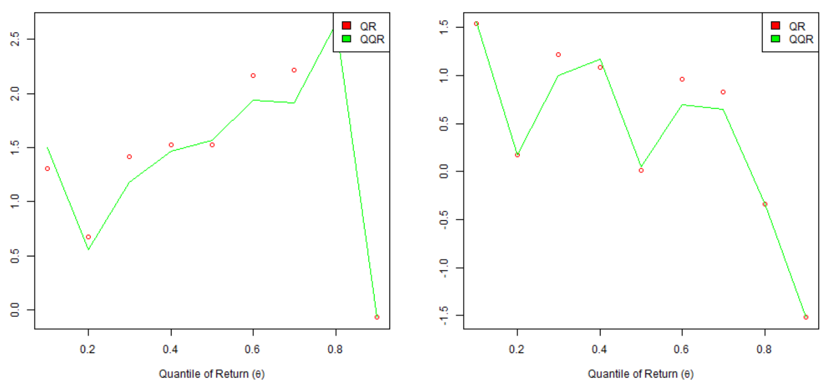
Energy and Resources



(a) Oil Industry (b) Utilities

Figure A7: QR QQR Comparison

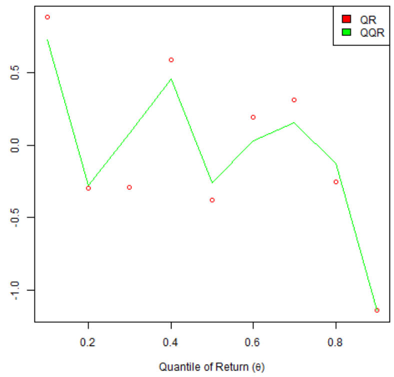
Automotive and Transportation



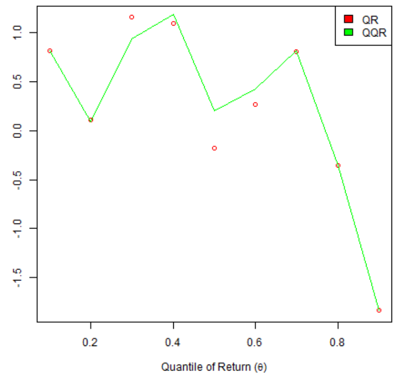
(a) Automobiles (b) Transportation

Figure A8: QR QQR Comparison

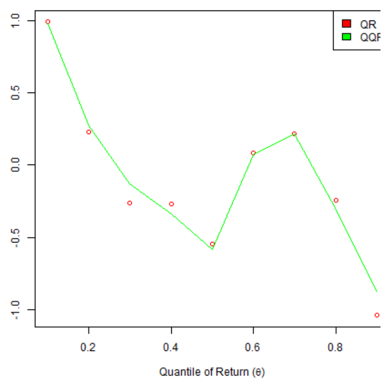
Manufacturing, Industrial, and Construction



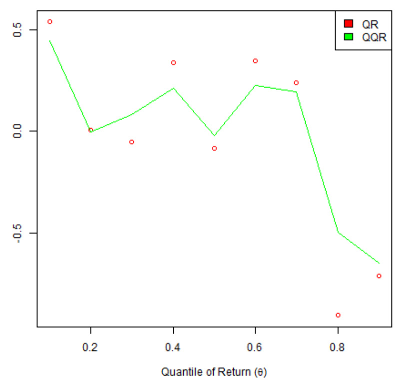
(a) Chemicals



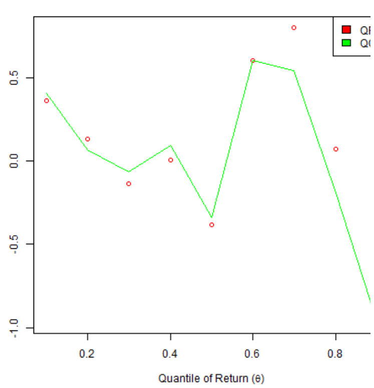
(b) Fabricated Products



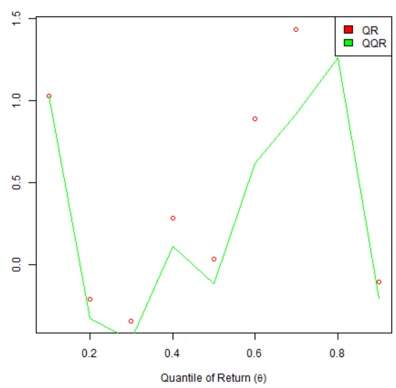
(c) Machinery and Business Equipment



(d) Mining and Minerals



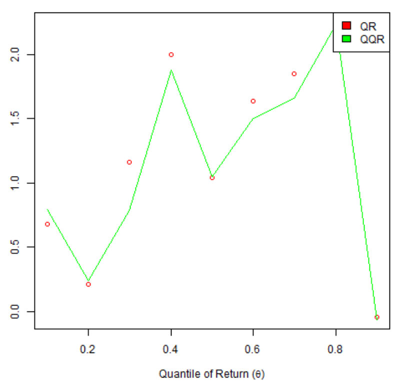
(e) Steel



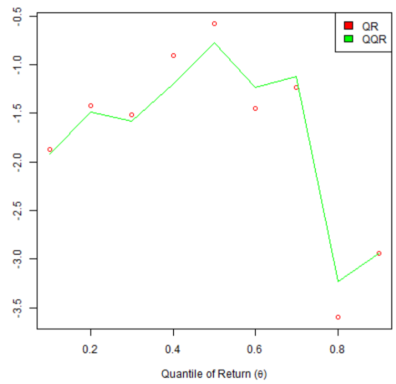
(f) Construction

Figure A9: QR QQR Comparison

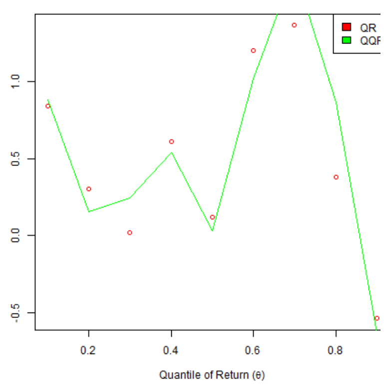
Consumer Goods and Retail



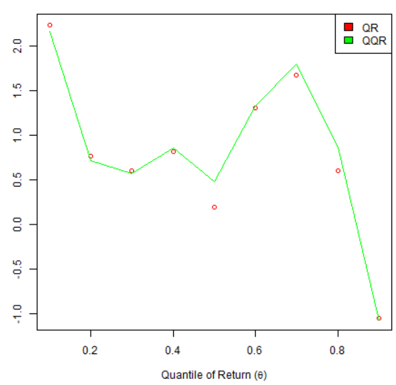
(a) Clothing



(b) Consumer Products



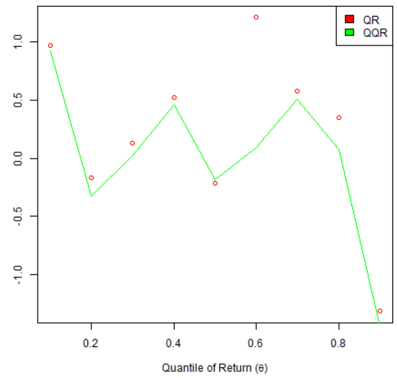
(c) Consumer Durables



(d) Retail Stores

Figure A10: QR QQR Comparison

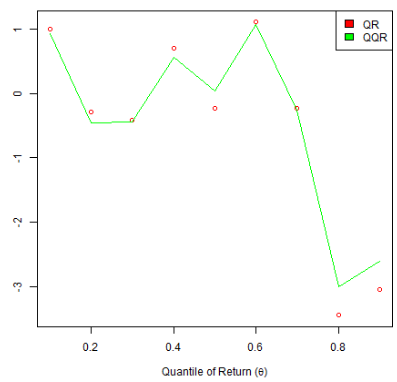
Financial and Insurance



(a) Financial and Insurance

Figure A11: QR QQR Comparison

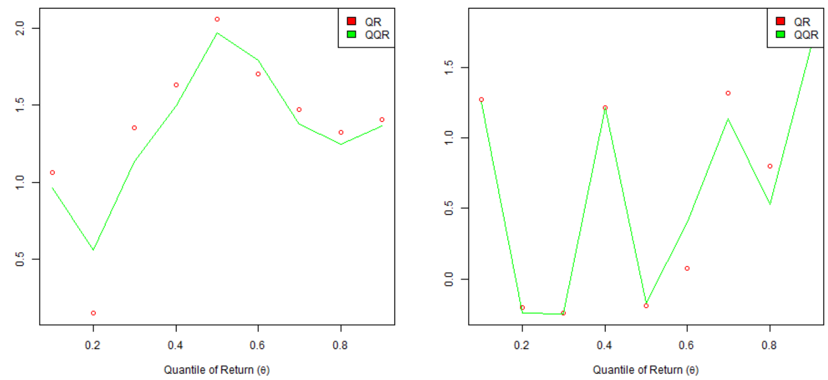
Food and Agriculture



(a) Food and Agriculture

Figure A12: QR QQR Comparison

Green Investment Fund



(a) NASDAQ CLEAN EDGE GREEN ENERGY (b) NASDAQ OMX Green Economy

Figure A13: QR QQR Comparison