FINANCIAL MANAGEMENT OF CLIMATE RISK IN EUROPE

Lucia García Villodre

Trabajo de investigación 023/005

Master en Banca y Finanzas Cuantitativas

Tutor:
Dra Pilar Soriano

Universidad Complutense de Madrid

Universidad del País Vasco

Universidad de Valencia

Universidad de Castilla-La Mancha

www.finanzascuantitativas.com

FINANCIAL MANAGEMENT OF CLIMATE RISK IN EUROPE

Master Thesis

Lucía García Villodre

Supervisor: Pilar Soriano Felipe (UV)

Master in Banking and Quantitative Finance

Universidad Complutense de Madrid

Universitat de València

Universidad del País Vasco

Universidad de Castilla-La Mancha

June 2023

Abstract

Following Engle et al. (2020), we use a mimicking portfolio approach as our main methodology in order to hedge climate risk in Europe. We will construct climate risk hedge portfolios by using trading assets in the Stoxx Euro 600 Index. Instead of buying a stock or derivative for hedging climate risk, we form a portfolio that manages to hedge climate change news period by period. In order to measure climate change news in Europe we will use the EU Climate Change News Index. When forming hedge portfolios, we take into consideration the three standard factors: size, value and market. Moreover, we contemplate an additional factor related to environmental scores. Our results are relevant for portfolio managers.

Keywords: Portfolio hedging; Risk; ESG; Climate Change; Forecasting

Acknowledgments

I would like to express my most sincere gratitude to my director, Pilar Soriano Felipe, for her continued help and valuable feedback. I am also very grateful to Ana Mª Ibañez Escribano for her support and her advice. I am truly thankful to Aron Hartvig Dénes for allowing us access to the index (ECCNI - Total) data and its components. Finally, I want to thank my friends, my partner and my family for their unconditional support along this road.

Contents

1 Introduction

Environmental (E), Social (S), and corporate Governance (G) risks are gaining importance in our society over time. Nowadays, investors, institutions and public in general are more and more concerned about climate change issues.

While there is not an agreement in the definition about climate risk, there have been numerous papers in the context of it and also its effects in economy and investment decisions. According to Giglio et al. (2021), climate change has considerable negative effects on future economic activity. They have considered climate change as one of the biggest challenges of our time. They also represent climate change as the risk of a relatively low-probability catastrophic event that could have a significant impact on the economy.

In fact, last decade, consequences of climate change on the planet have worsen. This topic has also gained evident importance in scientific debates in recent years, as well as in politics. Hence, it is necessary to first define climate risk as a concept. There have been a lot of definitions over the years. Climate risk could be related to physical consequences in the environment: we have clarifying examples in the sea-levels rise, the heating of the oceans or floods never seen before.

According to Aven (2020), climate risk is clearly correlated with transition risk, and their consequences are different depending on the agent. For example, companies would be more concerned about how climate change can affect in terms of profitability. This author explains that the main challenge is related to becoming a low-emission society and there can be consequences related to deviations to this objective. That is how we can understand transition risk.

In this context, it is necessary to mention the term *climate finance*. That concept also appears in Giglio et al. (2021) and it refers to the interrelationships between environmental and financial economics.

The former head of Bank of England, Mark Carney, stated in 2015 that climate change can affect financial stability trough three channels. The first one, as mentioned before, is related to *physical risks*. The former governor refers to the impact that weather-related events may have on financial assets. The next one, which we also mentioned earlier, relates to *transition risk*. The economist connects this risk to the possible impact of the process of becoming a low carbon economy, even leading to a change in the value of some assets. And finally, the head of Bank of England considered a third point, *liability risk*. This risk is linked to the possibility that people affected by climate change demand certain compensation in the near future. Also, liability risk is considered by the economist as one of the risks that cannot be predicted even using the most advanced models.

At the present time, institutions and investors are increasing their concern about how stock markets price climate change risks in an efficient way. As Battiston et al. (2021) defended, climate change is now recognised as a new source of financial risk. These authors have also pointed out that climate risk is systemic and non-linear and is characterised by fat tails. It can generate protracted crises over time with potentially profound implications for financial stability. Their article also emphasizes the need for investors and financial institutions to assess their exposure to climate risks. In other words, it reports on the importance of integrating climate change considerations into policy as well as financial risk assessment. In this context, multiple indicators have been defined to consider climate change effects in markets and also how to hedge them.

In this sense, the main objective of our study is to hedge climate risk in Europe. We use a mimicking portfolio approach as our main methodology. Firstly, we will construct climate risk hedge portfolios by using trading assets in the Stoxx Europe 600 index. It will be a dynamic hedge. Instead of buying an stock or derivative for hedging climate risk, we form portfolios that manage to cover climate change news period by period. In the process of forming these hedge portfolios we must consider some standard factors: size, value and market. These factors could be correlated with climate risk, but they are also important to explain returns. To construct them, we will use data about market capitalization and book-to-market ratios from the Stoxx Europe 600 index. In order to hedge climate change news in Europe, we are going to consider these factors and we also contemplate an additional factor related to environmental scores. Secondly, we will use the Fama-MacBeth methodology as an alternative method to form hedge portfolios. It will serve as a robustness test and it will also allow us to check if climate risk is actually taken into account in financial markets. We will describe this procedure in detail in the following sections.

Lamont (2001) describes a mimicking portfolio as a "portfolio of assets with returns that track an economic variable". In our case, the dependent variable will be *news* and it will contain information about changes in climate risk, meaning that our tracking portfolio will connect stock prices with news about climate risk.

As Roll & Srivastava (2018) defended, the mimicking portfolio has to be composed only of liquid and easily tradable assets. The portfolio is defined as a traded fund designed to replicate the factor sensitivities of a traded variable, for example, individual assets. It is also valid for a non-traded variable, for example, the case of macroeconomic variables.

Following Pukthuanthong et al. (2019), the mimicking portfolio method could be also understood as a time-series approach, where we use firms characteristics to construct factors and then they are regressed on returns of traded assets.

In reference to the environmental factor, Venturini (2022) defended that ESG investing is strictly related to climate change considerations by investors. In general, ESG ratings are divided in three pillars. In the first place, the "E" pillar is related to environmental topics, that is, it includes the effects that the activity of the companies could have on the environment, both directly and indirectly. Secondly, the "S" pillar refers to the impact that a company could have on society. And last,the "G" pillar is related to governance issues, for example the company's transparency. In this research, we use ESG scores to measure climate vulnerability of the companies. Therefore we add the "E" pillar score as a factor in our hedge portfolios.

As Cornell (2021) stated, ESG ratings could hedge climate shocks and also changes in regulation, specifically in terms of environment. Moreover, we have to take into account the disparity between different providers' ratings, which is not yet settled at the present time.

In this context, we can also mention the greenness and transparency factor based on companies in the Stoxx Europe Total Market Index constructed by Alessi et al. (2021). Being this study's scope certainly similar to ours, the authors use Bloomberg to obtain Environmental disclosure scores and construct the mentioned factor. Their main object differs from ours, but what matters to us is that they provide evidence about the existence of a pricing factor related to climate risk. Thus, in our study, we will try to hedge climate risk by implementing a mimicking portfolio approach. In particular, we will follow Engle et al. (2020) procedure.

Pástor et al. (2021) use a similar methodology, they considered a two-factor model: the market and an ESG factor. In their study, they considered that ESG preferences could move asset prices. They also defended that green stocks should hedge climate risk.

Once we form the hedge portfolio, we will check how well it hedges innovations of climate news. In their study, Engle et al. (2020) constructed an index that measures innovations in news about climate risk in US. That index is designed to proxy for the arrival of climate change information in US financial markets. This way, they are able to measure the news that are relevant for investors concerned about climate risks. In fact, they formed two indices: Wall Street Journal climate change news index and Crimson Hexagon's negative sentiment climate change news index. The first one captures the *attention* about climate change in the Wall Street Journal and the second one, as its name implies, focuses on negative climate news and could capture the *negative attention*.

We are assuming that equity prices are going to change if new climate change information arrives and for that reason we could construct a portfolio of stocks that can track news about climate risks. Ardia et al. (2022) formed a daily Media Climate Change Concerns index also using news about climate change. Their index is a a daily proxy that captures unexpected increases in climate change concerns in US.

In our case we will use the EU Climate Change News Index, proposed by Hartvig et al. (2023). That index allows us to capture the new information about climate change in the European mainland. The great advantage is that this index can be broken down into 5 sub-categories: Emissions, Fossil Fuels, Gas, Policy and Renewables. Therefore, the main contribution of our study is twofold: first, we construct the hedge portfolios for Europe, rather than for the US. Second, we are able to analyse separately the impact of news from each of the above sub-categories.

In summary, in the mimicking portfolio approach we are going to construct the hedge portfolios by using the mentioned factors. After, we will check if these portfolios manage to hedge the total index's innovations and its five groups respectively. At the end, what we are doing is to check whether climate risk is priced or not. Engle et al. (2020) have found evidence that climate risk is priced in U.S. On the contrary, others authors such as Pástor et al. (2021) or Ardia et al. (2022) have not found this evidence. Venturini (2022) offers an interesting literature review on this issue. In our study, we will try to find out if climate risk is priced or not in Europe.

To build hedge portfolios, instead of using the mimicking portfolio approach, we could use the Fama & MacBeth (1973) methodology as an alternative. We will do this as a robustness check. Huynh & Xia (2021) used the Fama and MacBeth regression approach but they focus on the US corporate bond market. In this study, they estimate the covariance between the mentioned bonds and a climate change news index: the Wall Street Journal Climate Change News Index. They found that bonds with a higher climate change news beta have lower future yields and this would lead to increased demand for bonds with a high potential to hedge against climate risk.

Also in the context of Fama-MacBeth, we can mention the recent study published by Zhang et al. (2023). They analyse the role of climate risk in cross-sectional pricing. Their study focuses on the Chinese stock market and they have constructed the climate risk factor through the climate political uncertainty indicator (CPU). We can think about some similarity between this indicator and the EU Climate Change News Index. The CPU is also built from news, specifically it is based on the eight major US newspapers. This is how they can measure risks related to climate change. In their study, they also include other variables (illiquidity, the rate of return on capital and company's annual growth rate of assets).

The remainder of this paper is organized as follows. In section 2, we present our sample by describing data and their characteristics. In section 3, we form hedge portfolios following a mimicking portfolio approach. In section 4, we provide results in and out of sample. In the following section 5, we do some robustness checks using the Fama-MacBeth methodology and also adding ETFs returns to the mimicking portfolio approach. And, finally, section 6 concludes.

2 Data

2.1 EU Climate Change News Index

Our main objective is to hedge climate change news in Europe. To achieve this goal first we need to obtain a measure for the European Union. We got that measure from the EU Climate Change Index recently published by Hartvig et al. (2023).

In this study, their authors create a EU Climate Change News Index (ECCNI) by converting online news articles to significant variables. They have used GDELT database. It is defined as an open platform with a wide selection of daily news from different countries.

ECCNI is constructed with daily news, obtained from the mentioned database, by using almost 30,000 articles related to EU questions and policies. Furthermore, they have classified news in five main groups: fossil fuels, renewable energy, energy policy, emissions and gas. And they gave scores to these categories using a Term Frequency–Inverse Document Frequency (TF–IDF) matrix. At last, they create the total EU Climate Change News Index as the aggregated score of the groups mentioned. In essence, they have formed that index by using climate change-related keywords. As a result they got a measure that is able to follow the debate on climate change in the European territory. At the end, they have shown that incorporating this index into a prediction model significantly increases the price forecasts of the EU Emissions Trading System (the first international carbon market in the world).

We use the ECCNI index to form our dependent variable.We scale this index by a factor of 10 so that the innovations we will build can be more easily interpretable. We will use daily observations between January 1, 2017, and December 31, 2022. From these observations, we construct monthly data as the mean value of index observations for each month. As a result, we obtain 72 observations of the index and we also repeat this for the five main groups already mentioned.

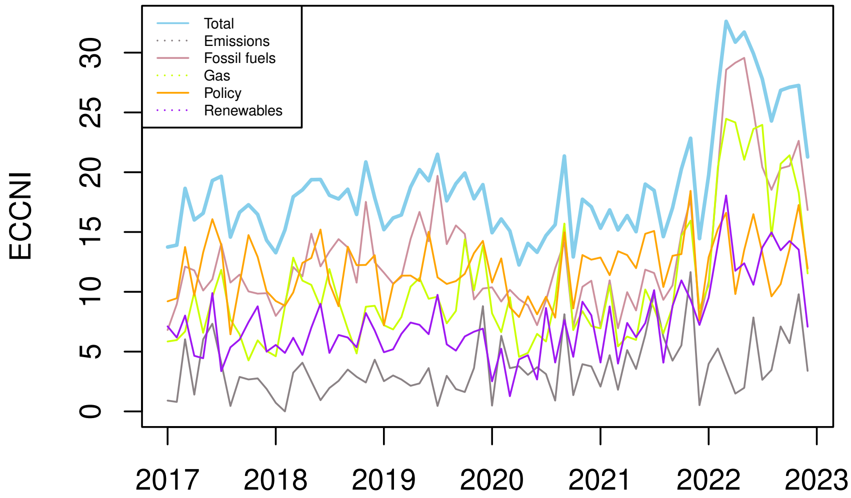


Figure 1: Monthly score history for ECCNI total and five main groups in the 2017-2022 period.

In Figure 1 we can observe the evolution of the total Index and also its five subcategories. First, it is necessary to mention the ECCNI is quite volatile.

In the middle of 2017 we observe a peak. This may be related to the fact that on June 1, 2017, Donald Trump announced his intention to withdraw the US from the Paris Agreement. It may also be related to the excessively high temperatures that were recorded in much of Western Europe in June 2017.

In March 2020 the index began to decrease as a result of the COVID-19 pandemic becoming the main topic of the news published at that time. However, at the end of that same year, we can observe a peak in the total index and also in in the policy category. That may be related to the Summit for Climate Ambition that took place in December 2020 virtually. It represented a great advance in climate matters. Seventy-five leaders from different countries from all the continents of the world met and outlined a series of new commitments. Moreover, we can observe a similar peak in the total index and also in the policy category at the end of 2021. This fact may be related to the United Nations Conference on Climate Change (COP26), held in Glasgow (Scotland) in November 2021.

This agreement was described as insufficient according to the United Nations.

Finally, we can easily notice that the ECCNI gets its maximum on February, 2022. It can be associated to the beginning of the armed conflict between Russia and Ukraine. This event affects specifically two groups: fossil fuels and gas. It makes sense because these commodities have been obviously affected by the war. In general, EU Climate Change News index is a measure that can reflect the impact of climate events in news.

2.2 Stocks in hedge portfolios

Once we have presented the variable that represents climate change news, the next step for implementing the mimicking portfolio approach is to define the set of stocks that is going to form our sample. For that purpose, we have obtained data from European assets. Specifically we obtain monthly individual stock return data. It is necessary to work with monthly data because we are going to build hedge portfolios. It makes sense to rebalance with this frequency.

We have collected data from Eikon Refinitiv. To form our sample, we have included firms traded on the Stoxx Europe 600 index in the period between 01/01/2017 and 31/12/2022. This index contains large, mid and small companies from 17 different European countries. We have obtained data about close price, market capitalization and book-to-market ratio from the companies mentioned, being these data required to form the standard factors (size, market and value).

Following Amihud (2002) procedure, we exclude some stocks. At first, we should omit *penny* stocks, defined as "stocks with a price below $5 at the time of portfolio formation". In our case, we have done the equivalence in euros. The reason for this exclusion is the existence of stock market microstructure and its derived problems related to information asymmetry, incomplete markets, market architecture and market transparency, among others.

We can relate market microstructure to the existence of trading costs. When we have to price stocks we usually assume market efficiency (no cost and no frictions), however the truth is rather different. These costs are present in comissions and also in the bid-ask spread as Stoll (2003) explains.

In addition, we need to include a second filter in our sample to omit *microcap* stocks.

These type of assets are defined by Engle et al. (2020) as "stocks with a market capitalization in the bottom 20% of the sample".

Based on this, we obtain the 20th percentile to exclude firms whose market capitalization has been below this percentile at any point of time. The justification for this exclusion is to relieve the impact of small stocks and the presence of anomalies in their average returns. Furthermore, we need to omit *microcaps* because they could dominate the regressions we will estimate afterwards, they could have more extreme values.

It is necessary to consider that we are going to work with excess yields. In our case, we have selected the 10-year German bond yield to obtain data on the risk-free interest rate. So, from now on, when we refer to returns, we understand that we have already considered this risk-free rate. In other words, we work with excess returns.

2.3 Climate risk exposure

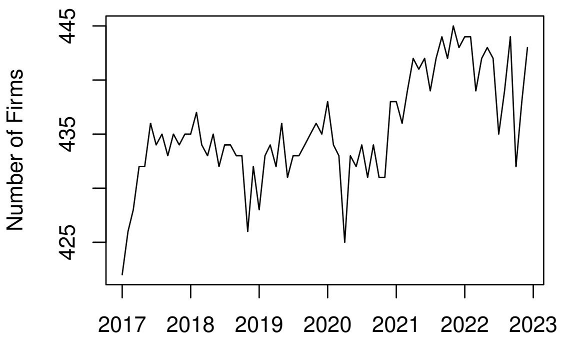
As we have already defined, we are going to consider an additional factor from the ESG scores of the companies. Specifically, we add the "E" pillar score to measure companies' climate risk exposure. We have obtained ESG scores data from firms traded on Stoxx Europe 600 index between 2017 and 2022. The ESG scores data, also provided by Eikon Refinitiv, range between 0 and 100 and have an annual basis.

By following Eikon Refinitiv's methodology, we present ESG ranges of scores and their description.

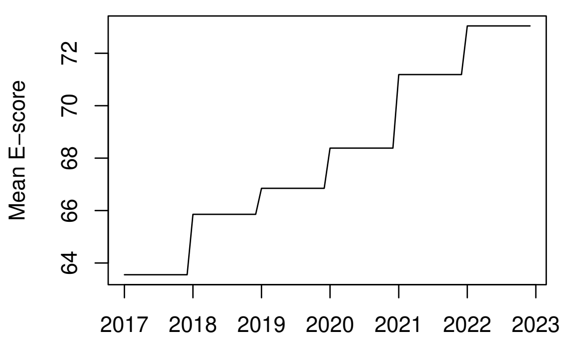
Table 1: ESG scores range in Eikon Refinitiv.

Range of scores	Quartile	Description
From 0 to 25	First	Poor ESG performance and not sufficient transparency in public reports of ESG data.
> 25 to 50	Second	Satisfactory ESG performance and a moderate degree of transparency in public reports of ESG data.
>50 to 75	Third	Appropriate ESG performance and higher than average transparency in public reports of ESG data.
> 75 to 100	Fourth	Brilliant ESG performance and a high transparency in public reports of ESG data.

In our sample, the companies with highest E-score are Assicurazioni Generali SpA, ABB Ltd, Stellantis NV, UBS Group AG and Alstom SA. These companies have a score above 90, that is to say, they have an excellent relative environmental performance. On the contrary, we find VAT Group AG, Investor AB, L E Lundbergforetagen AB, United Internet AG or Cts Eventim AG & Co KgaA as the companies with lowest E-score. In the case of these companies, their score has been below 10. In other words, they have a poor relative environmental performance as well as insufficient transparency in environmental data reporting.



(a) Number of firms over time.



(b) Mean over time

Figure 2: E-scores over time.

In Figure 2a we can observe the number of firms in our sample. We can observe that the number changes throughout the sample period as a result of the filtering described in Section 2.2.

Figure 2b represents the average values of the E-scores for a constant set of assets that we can observe throughout the sample period. This set is composed by 303 firms. We observe that the mean is between 60 and 70 over the years. We can understand that, on average, firms in our sample have an appropriate E performance. We can also observe that, over the years, we obtain a higher average E-score. This may be because in recent years companies have begun to take ESG criteria more into account.

For this type of data, we could also have used other data providers. For example, we could use MSCI KLD scores to evaluate firm's environmental performance. These scores are in the same range as the aforementioned Eikon Refinitiv scores. Also, we can mention Sustainalytics, which provides a new ESG Risk Rating. That is a measure about company's exposure to ESG risks and how well a company is managing those risks. These ratings take into account both exposure and risk management. For each company, non-managed risk is measured by evaluating a set of problems based on these two aspects. The ESG risk rating of a company has on the one hand a quantitative score and on the other hand a risk category. Such a score represents units of non-managed ESG risk, so lower scores represent less not managed risk. This measure works in the opposite way to the ESG scores from Eikon Refinitiv. Unfortunately, we did not have access to this alternative data, and we could not use data provided from other databases.

2.4 European Fama and French factors

As we have mentioned, we are going to use a second approach to check if the climate risk factor is significant. To apply the Fama-MacBeth methodology we need to define the factors that we are going to consider. As we have stated above, we use the EU Climate Change News Index innovations as an additional factor. But we need to include other factors that represent the sources of market risk for the geographic area on which our study is focused. For that aim, we obtained the three factors from Fama and French official website for Europe. These factors are the following: SMB (size), HML (value) and market risk. They have obtained these factors for different regions. To form the three European factors, Fama and French include data of the following countries: Austria, Belgium, Switzerland, Germany, Denmark, Spain, Finland, France, the United Kingdom, Greece, Ireland, the Netherlands, Norway, Portugal and Sweden.

In the following section we will explain in more detail how these three factors (market, SMB and HML) are formed.

3 Methodology

3.1 Mimicking portfolio approach

In this section, we are going to construct hedge portfolios for climate change news innovations. As we have mentioned, we are going to use the mimicking portfolio approach following Engle et al. (2020). This methodology consists in replicating the news index innovations (I_t^{ECCNI}) by regressing firm's returns (r_t) weighted by the different matrices of firm's characteristics (Z^{E}, Z^{SIZE}, Z^{VALUE} and Z^{MARKET}).

At first, we need to construct innovations in climate news. In Section 2.1, we average the daily values for EU Climate Change News Index and obtain 72 monthly observations of the index. We also repeat this process for the five main groups already described (fossil fuels, renewable energy, energy policy, emissions and gas). Once we have monthly values, we can form innovations in climate news as the residuals from an AR(1) model. We refer to them as I_t^{ECCNI} and we will specify which group it is. For example, if it is related to the total index $I_t^{\text{ECCNI total}}$ or $I_t^{\text{ECCNI gas}}$ for news related to the gas group or subcategory.

As a result of forming these innovations, we have 6 hedge targets (one for the total and another five for the subcategories described). We can start applying the mimicking portfolio approach. As it has been explained above, we form these hedge portfolios by considering the three standard factors and also an additional factor related to E-scores. In this section we are going to explain how we have constructed these factors. Hereafter, we will refer to them as the "Z" or the characteristics matrix. We will have a matrix for each factor, which in each case will consist of 72 rows for time and N columns for firms.

In a first step, we construct matrix Z^{E} in order to capture the firms' climate risk exposure described in Section 2.3. Following Engle et al. (2020) methodology, we could use two different ways:

(a) Using the demeaned absolute value of the E-scores from our firms (Z^{E1}).

(b) Using the standardized E-scores, rescaling them between -0.5 and $+0.5$. The company with the highest score will have a score equal to $+0.5$ and on the opposite side the company with the lowest score will have a score equal to -0.5 (Z^{E2}).

Despite the differences between both approaches to get matrix Z^{E}, the firms with higher and lower score are the same in both cases. But we have to consider that those matrices are in completely different ranges.

Next, we can form the three standard factors: size, value and market, using the data described in Section 2.2. The first fundamental factor is related to size, Z^{SIZE}. To obtain the size characteristic matrix we use a standardized market capitalization value. This way, half the firms will have positive weight (long position) and the other half will have negative weight (short position). In terms of the second fundamental factor, we form Z^{VALUE} by standardizing book-to-market ratio data. Lastly, we obtain the market matrix Z^{MARKET} by calculating the share of total market value.

Following Engle et al. (2020), once we have formed our Z characteristic matrices, we can form the hedge portfolio as follows.

$$\begin{aligned} I_t^{\text{ECCNI}} =& \xi + w_{\text{SIZE}} Z_{t-1}^{\text{SIZE}'} r_t + w_{\text{VALUE}} Z_{t-1}^{\text{VALUE}'} r_t \\ &+ w_{\text{MARKET}} Z_{t-1}^{\text{MARKET}'} r_t + w_{\text{E Scores}} Z_{t-1}^{E'} r_t + e_t \end{aligned} \tag{1}$$

Where I_t^{ECCNI} can refer either to the total index or to one of the five groups mentioned above. And $Z_{t-1}^{E'}$ refers to one of the two ways already described to measure firms' climate risk exposures. We are going to use the Ordinary Least Squares method for the six regressions, one for the total index and the other five relating to the categories Emissions, Fossil, Gas, Policy and Renewables.

In each regression, we are going to form four portfolios based on the different characteristics we have already mention (size, value, market and climate). And that is how we build the mimicking hedge portfolio for the corresponding I_t^{ECCNI}. In relation to the four portfolios formed to build the hedge portfolio, we can rename them. For example, the portfolio based on size, $Z_{t-1}^{SIZE'} r_t$, can be renamed as $\tilde{\mathrm{r}}_t^{SIZE}$.

So we can rewrite equation 1 as follows:

$$I_t^{\text{ECCNI}} = \xi + w_{\text{SIZE}} \tilde{\mathrm{r}}_t^{SIZE} + w_{\text{VALUE}} \tilde{\mathrm{r}}_t^{VALUE} + w_{\text{MKT}} \tilde{\mathrm{r}}_t^{MKT} + w_{\text{E Scores}} \tilde{\mathrm{r}}_t^{\text{E1}} + e_t, \tag{2}$$

Equation 2 refers to the regression by using the first way to capture firm's climate risk exposure. And the independent variable I_t^{ECCNI} will change depending on whether we use the total or one of the five categories. As a result of each regression, we will obtain the estimations of w_{SIZE}, w_{VALUE}, w_{MARKET} and $w_{\text{E Scores 1}}$.

Equation 3 is rewritten using the second way to obtain firm's climate risk exposure.

$$I_t^{\text{ECCNI}} = \xi + w_{\text{SIZE}}\tilde{\text{r}}_t^{SIZE} + w_{\text{VALUE}}\tilde{\text{r}}_t^{VALUE} + w_{\text{MKT}}\tilde{\text{r}}_t^{MKT} + w_{\text{E Scores}}\tilde{\text{r}}_t^{\text{E2}} + e_t \tag{3}$$

As a result of each regression, we will obtain the estimations of w_{SIZE}, w_{VALUE}, w_{MARKET} and $w_{\text{E Scores}}$. Once we have the estimated weights, we can get the hedge portfolio's excess returns for I_t^{ECCNI} as follows:

$$h_t^{\text{I}} = \hat{w}_{\text{SIZE}}\tilde{\text{r}}_t^{SIZE} + \hat{w}_{\text{VALUE}}\tilde{\text{r}}_t^{VALUE} + \hat{w}_{\text{MKT}}\tilde{\text{r}}_t^{MKT} + \hat{w}_{\text{E Scores}}\tilde{\text{r}}_t^{\text{E}} \tag{4}$$

There are two ways to interpret these weights. They can be understood as the weight of the corresponding portfolios in the hedge portfolio for the innovations of each index. Alternatively, along with the Z's constructed for each characteristic, they can be interpreted as weights that change over time ($\hat{w}Z'_{t-1}$).

Once we have estimated these weights, we can determine the weight of each firm in the hedge portfolio. With this purpose, we build the following sum:

$$\hat{w}_{SIZE}Z_{i,t}^{\text{SIZE}'} + \hat{w}_{VALUE}Z_{i,t}^{\text{VALUE}'} + \hat{w}_{MKT}Z_{i,t}^{\text{MKT}'} + \hat{w}_{E}Z_{i,t}^{\text{E}'} \tag{5}$$

Where the $\hat{w}$ are the coefficients estimated in the regressions described above. In other words, we can affirm that the company's weight in the hedge portfolio formed will be determined by its E-Score, its size and its value ratio.

3.2 Fama-MacBeth approach

Fama-Macbeth methodology is based on risk factors. In the previous section we have described the factors included as well as the process for obtaining them. We will first include a climate risk factor formed by the residuals of an AR(1) model on the EU Climate Change News Index (I_t^{ECCNI}). However, we are going to consider the existence of multiple factors or sources of systematic risk that cannot be internalized through the market portfolio. Each of these sources of risk will affect assets to a different extent.

This is because, by definition, they represent systematic or non-diversifiable risk factors. To consider the different sources of risk, we will include the three traditional Fama and French factors: size (SMB), value (HML) and market.

Before explaining the methodology, we are going to describe how these factors are formed. For this description we will rely on Fama & French (1995).

The first factor is related to the excess return on a market portfolio. It is calculated as the difference between market return and risk free return. In other words, we are considering a long position in the market portfolio and a short position in the risk-free asset. As a result, this factor manages to replicate the market risk.

For the following two factors, it is necessary to sort the stocks that belong to the considered region, Europe in our case. Fama and French consider two groups based on median market capitalization: small and big. Similarly they have formed three groups using ranked values of book-to-market ratio. As a result of the intersection of the aforementioned groups, they obtain six value-weighted portfolios: SG, SN, SV, BG, BN and BV. On the one hand, S and B indicate small or big. And on the other hand, G, N and V indicate growth (low book-to-market ratio), neutral and value (high book-to-market ratio).

Once they have formed those groups, they obtain the SMB (small minus big) factor that is linked to size. That factor can be understood as the equal-weighted average of the three small stock portfolios' returns for the region minus the average of the three large stock portfolios' returns.

The third factor is HML (High minus Low), that is related to the book-to-market ratio. That factor can be understood as the equal-weighted average of the two high book-to-market portfolios' returns of minus the average of the two low book-to market portfolios' returns.

Once we have compiled the four factors that we are going to consider, we can describe the two steps necessary for this approach. The first is to estimate the betas associated with each factor. These estimates are obtained through a time series regression of factor returns. These coefficients can be interpreted as *risk exposures*. The exposure to each factor will be different for each stock. For that reason, we are going to obtain the estimated betas for each of the considered assets or firms (i).

We can express the regression as follows:

$$r_t^i = \alpha^i + \beta_I^i I_t^{\text{ECCNI}} + \beta_{mkt}^i Mkt_t + \beta_{SMB}^i SMB_t + \beta_{HML}^i HML_t + u_t \tag{6}$$

As a result of these regressions, we obtain one beta for each company and for each factor we have considered. Therefore, we will have as many observations for each beta as companies we have in the sample (N). In other words, $\hat{\beta_I}$, $\hat{\beta_{mkt}}$, $\hat{\beta_{SMB}}$ and $\hat{\beta_{HML}}$ will be vectors of dimensions 1xN.

The second and last step consists of obtaining the coverage portfolios for each of the factors considered. These portfolios are obtained at each available time t through cross-section OLS regressions of the returns on the betas estimated in the previous step.

$$r_t = h_t^I \hat{\beta}_I + h_t^{mkt} \hat{\beta}_{mkt} + h_t^{SMB} \hat{\beta}_{SMB} + h_t^{HML} \hat{\beta}_{HML} + e_t \tag{7}$$

As a result of this approach, we get h_t^I, h_t^{mkt}, h_t^{SMB} and h_t^{HML} hedge portfolios returns. They are obtained period by period by using cross-sectional regressions of asset returns onto exposures to the risk factors. These hedge portfolios will have, by definition, beta equal to one with respect to their corresponding factor. And on the contrary, they will have zero beta with respect to the rest of the factors.

It is necessary to mention that we are going to apply this methodology making use of the total ECCNI for the climate risk factor. But we also are going to use the five index's sub-categories already mentioned above (Emissions, Fossil, Gas, Policy and Renewables).

4 Results

4.1 In-sample

In this section we present the in-sample results of the regressions already described in the mimicking portfolio approach section. The following tables summarize the results obtained in-sample, where the dependent variable captures innovations of the EU Climate Change News Index and each of the five groups already described. As we have mentioned, we use monthly frequency and the sample runs between January 2017 and December 2022. In the following tables we can find the weights estimated for each case, and standard errors are presented in parentheses. The significance is also represented as follows: * if p-value is lower than 0.1; ** if p-value <0.05 and *** if p-value <0.01.

Table 2: Regression: ECCNI using E method 1.

	Total	Emissions	Fossil	Gas	Policy	Renewables
Constant	0.2168	1.2010***	0.5902	0.7165*	0.62985	0.5017
	(0.3366)	(0.3427)	(0.4121)	(0.4282)	(0.4046)	(0.3558)
$\tilde{r}_t^{SIZE}$	2.4000**	2.6890**	0.9574	1.5710	2.3130*	0.1680
	(1.1350)	(1.156)	(1.3900)	(1.4440)	(1.3650)	(1.2000)
$\tilde{r}_t^{VALUE}$	0.1570	0.4745	0.1245	0.2312	0.3796	0.3789
	(0.3666)	(0.3733)	(0.4488)	(0.4664)	(0.4407)	(0.3876)
$\tilde{r}_t^{MARKET}$	−1.2910**	−1.4830**	−0.5010	−0.9017	−1.2070	−0.1102
	(0.6131)	(0.6243)	(0.7506)	(0.7800)	(0.7370)	(0.6482)
$\tilde{r}_t^{E1}$	0.00002	−0.00008	−0.000007	−0.00004	−0.00003	−0.00006
	(0.00007)	(0.00007)	(0.00008)	(0.00008)	(0.00008)	(0.00007)
R-squared	0.09347	0.07925	0.00914	0.02638	0.05605	0.02818

This table shows results from equation 2 by using the demeaned absolute E-scores. The dependent variable captures innovations for the EU Climate Change News Index and the five sub-categories. Standard errors are presented in parentheses. The significance is represented as follows: * if p-value is lower than 0.1; ** if p-value <0.05 and *** if p-value. <0.01.

This table shows results from equation 2 when hedging innovations to the EU Climate Change News Index and its five main groups. Column 1 shows that portfolios based on the demeaned absolut E-scores have not a significant relationship with $I_t^{\text{ECCNI total}}$. We can observe this same behavior in the five subgroups considered.

In addition to the E-scores, we can observe an apparent significant relationship between size and climate risk exposure in the following categories: Total, Emissions and Policy. In other words, we can understand that larger firms are less exposed to climate change news than smaller ones. That could be understood as larger companies performing better when the amount of climate change news index's innovations increases.

We can also observe a negative relationship between market and climate risk exposure.

That means that firms with a higher correlation with the market are less exposed to climate change news innovations. We can understand it as the greater the share of the total market value of a company, the less affected it will be by news about climate change in general. This relationship is significant in two of the six hedge targets we have analyzed, Total and Emissions.

If we observe the R-squared measures of these cases, the first column shows that the portfolio can hedge about a 9% of the variations in EU Climate Change News Total Index innovations. While for the rest of the categories analyzed, the R-square measures of the regressions are lower.

Once we have analyzed the results obtained to hedge climate news by using the demeaned absolut E-scores, we proceed to analyze the results by using the rescaled E-scores.

Table 3: Regression: ECCNI using E method 2.

	Total	Emissions	Fossil	Gas	Policy	Renewables
Constant	0.12394	1.01774***	0.50463	0.61402	0.50300	0.48639
	(0.33729)	(0.32393)	(0.41446)	(0.42897)	(0.40134)	(0.36277)
$\tilde{r}_t^{SIZE}$	2.32705**	1.62516	0.68297	0.98391	1.75409	−0.31418
	(1.04657)	(1.00510)	(1.28600)	(1.33104)	(1.24529)	(1.12562)
$\tilde{r}_t^{VALUE}$	0.66773*	1.05016***	0.49831	0.55806	0.86260**	0.24359
	(0.34241)	(0.32884)	(0.42074)	(0.43548)	(0.40742)	(0.36827)
$\tilde{r}_t^{MARKET}$	−0.80383	0.24410	0.12086	0.05857	−0.15737	0.36293
	(0.68246)	(0.65541)	(0.83859)	(0.86795)	(0.81204)	(0.73400)
$\tilde{r}_t^{E2}$	−0.00888	−0.02110***	−0.00900	−0.01179	−0.01394*	−0.00332
	(0.00636)	(0.00611)	(0.00781)	(0.00809)	(0.00756)	(0.00684)
R-squared	0.11746	0.20247	0.02828	0.05263	0.09960	0.02091

This table shows results from equation 3 by using the rescaled E-scores. The dependent variable captures innovations for the EU Climate Change News Index and the five sub-categories.Standard errors are presented in parentheses. The significance is represented as follows: * if p-value is lower than 0.1; ** if p-value <0.05 and *** if p-value. <0.01.

This table shows results from equation 3 when hedging EU Climate Change News Index and its five groups. Column 1 shows show that the portfolio based on rescaled

E-scores has not a significant relationship with $I_t^{\text{ECCNI total}}$.

However, we find a negative and significant relationship when hedging EU Climate Change Emission News Index innovations ($I_t^{\text{ECCNI emissions}}$). In other words, in periods with more innovations in climate news about emissions, a portfolio that has long positions in companies with higher E-scores will have a relatively lower excess return. We also find this negative and significant relationship when hedging EU Climate Change Policy News Index innovations ($I_t^{\text{ECCNI policy}}$), i.e. a portfolio that goes long in greener companies has a relatively lower excess return.

In addition to the E-scores, we can observe an apparent significant relationship between value and climate risk exposure in the following categories: Total, Emissions and Policy. In other words, we can understand that firms with a higher book-to-market are less exposed to climate change news than firms with a low book-to-market ratio. That could be understood as companies with a higher book-to-market ratio performing better when the amount of climate change news index's innovations increases.

About the R-squared measures, Emissions' column shows that the portfolio can hedge about 20% of the variations in EU Climate Change Emissions News Index innovations. While Policy's column shows that the portfolio can hedge almost 10% of the variations in EU Climate Change Policy News Index innovations.

We can compare the results obtained in the two cases. As in Engle et al. (2020), we get a considerably higher R-squared when we use the rescaled E-scores instead of using the demeaned absolute E-scores. This fact is true both when we use the total index as well as the five groups already mentioned.

It is necessary to mention that we have obtained significantly different results from those obtained by Engle et al. (2020) for the US. We have found a negative relationship between E-scores with index's innovations in Europe, while they observed otherwise for U.S. This might be explained because we are using a different sample period that is influenced by different types of news (2009 to 2016 vs. 2017 to 2022). Recall that news can be either good or bad news. For example, we can mention that in recent years natural disasters have become more frequent and their consequences worse, which might influence the relative ratio of negative news in our sample period. We were not able to distinguish between both (good or bad news), as we do not have a negative news index available for

Europe. We leave this for further research.

Next we focus on knowing how the implicit hedge portfolios would be composed in the regressions analyzed. To determine the weight of each firm in the hedge portfolio, we build the sum already described in equation 5. We present the average portfolio positions for the two categories where we have obtained significance: Emissions and Policy. We only present the portfolio's composition for EU Climate Change Emissions News Index because it looks very similar to the portfolio's composition for EU Climate Change Policy News Index.

Table 4: Largest short and long positions to hedge EU Climate Change Emissions News Index

Top positive portfolio weights	Top negative portfolio weights
Avanza Bank Holding AB	Stellantis NV
Diploma PLC	Alstom SA
L E Lundbergforetagen AB	Abb Ltd
Games Workshop Group PLC	Eiffage SA
Freenet AG	UBS Group AG
Inchcape PLC	Kering SA

This table shows the firms with the largest average short and long positions in the estimated hedge portfolios resulting from equation 3 presented in Table 3.

In Table 4 we can observe the top firm's weights when hedging EU Climate Change Emission News Index where we have found significance in the variables value and E-scores.

Based on the Global Industry Classification Standard (GICS), we can mention the importance of the *Financials* sector in the top positive weights. Avanza Bank Holding AB and L E Lundbergforetagen AB belong to this sector. In addition, the presence of the *Consumer* sector stands out, which includes companies such as Inchcape PLC and Games Workshop Group PLC. On the contrary, in the top negative weights we can highlight the *Industrials* sector where we find Alstom SA, Abb Ltd and Eiffage SA.

4.2 Out-of-sample

In this section we check the abilty of the hedge portfolio to hedge out-of-sample. In other words, we are going to check if the formed portfolios are capable of hedging index's innovations in months that were not included in the estimation portfolio composition.

With this purpose, we run the regression described in equation 1 for every period t by using data between periods $t_{\min}$ and $t-1$. We can understand $t_{\min}$ as the first observation in our sample that corresponds to January 2017. However we need a certain minimum of data to estimate the mentioned regression. We will use $t_{\min+30}$, that corresponds to June 2019. Then, we can form the hedge portfolio based on these estimations.

We could do this out-of-sample fit for equations 2 and 3. However, based on the results obtained in Section 4.1, we are going to focus in equation 3 by using the rescaled E-scores. Also based on these results we will check out-of-sample fit for the EU Climate Change Emissions News Index and the EU Climate Change Policy News Index innovations.

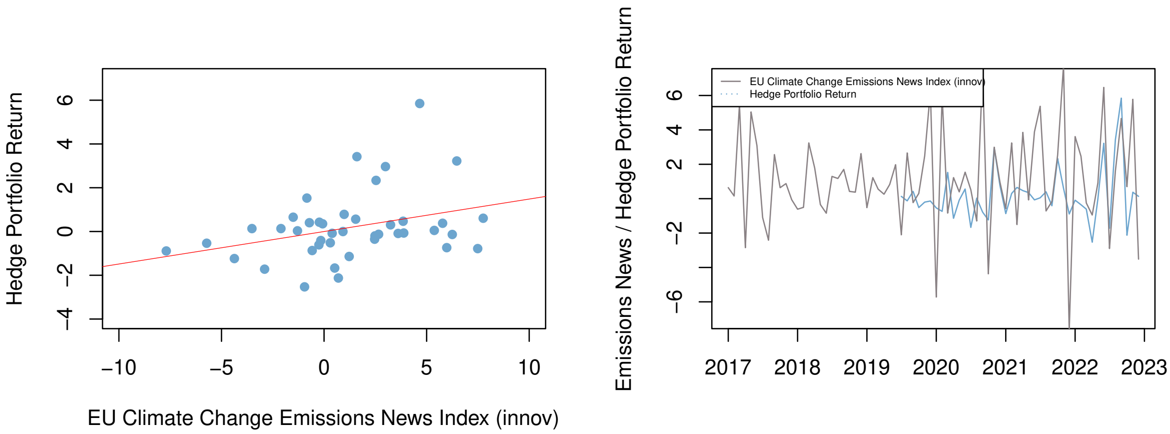


Figure 3: EU Climate Change Emissions News Index hedge portfolio (out-of-sample).

Figure 3 shows the out-of-sample performance of the hedge portfolio for innovations in the EU Climate Change Emissions News Index. The left graphic is a scatterplot of the out-of-sample hedge portfolio's returns together with the innovations in the mentioned index. The right graphic shows the time series of the innovations in emissions news and the return of the hedge portfolio. We can get the correlation between the hedge portfolio return and index's innovations, and in this case there is a clear and positive out-of-sample correlation equal to 0.33. In other words, hedge portfolio have high returns during periods with positive innovations in climate news.

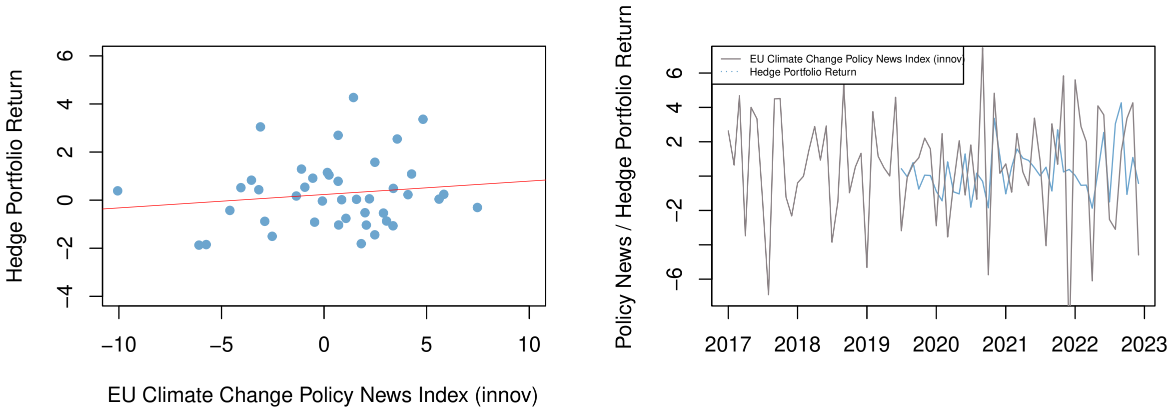


Figure 4: EU Climate Change Policy News Index hedge portfolio (out-of-sample).

Figure 4 shows the out-of-sample performance of the hedge portfolio for innovations in the EU Climate Change Policy News Index. The left graphic is a scatterplot of the out-of-sample hedge portfolio's returns together with the innovations in the mentioned index. The right graphic shows the time series of the innovations in emissions news and the return of the hedge portfolio. We can also get the correlation between the hedge portfolio return and index's innovations as we have done before. For Policy news we also obtain a clear and positive out-of-sample correlation equal to 0.14.

5 Robustness checks

5.1 Fama-MacBeth approach

We will now check if we can hedge index innovations by using the Fama-MacBeth approach. Based on the results obtained in the previous sections, we will only apply this approach for the EU Climate Change Emissions News Index and the EU Climate Change Policy News Index.

For that purpose, we use a sample formed by a constant set of assets that we can observe throughout the sample period. This set is composed by 303 firms.

In order to follow the Fama-MacBeth methodology we need to split our sample in two periods: estimation period (01:2017 to 12:2020) for the first step and testing period (01:2021 to 12:2022) for the second step.

First, we get the results for the EU Climate Change Emissions News Index. We use index innovations ($I_t^{\text{ECCNI Emissions}}$) in the regression described in equation 6. As a result of this first step, we get the estimated betas for each firm in the sample. We obtain that the beta related to the climate change factor is significant for 27 out of 303 companies. Secondly, we obtain the results for the second step by applying equation 7 and we obtain the hedge portfolio return for each factor. Specifically, we focus on $h_t^{\text{I emissions}}$ that can be understood as the portfolio's return to hedge EU Climate Change Emissions News Index innovations. We need to check if this time series is significantly different from zero. With this aim, we obtain the t-statistic for testing the hypothesis that $h_t^{\text{I emissions}} = 0$, to see if the price of climate risk is significant. In this case, the t-statistic is equal to 0.0005 and the p-value is 0.999. Hence, we cannot reject the null hypothesis.

We repeat this process for the EU Climate Change Policy News Index innovations ($I_t^{\text{ECCNI Policy}}$) by following the two steps already described. As a result of this first step, we obtain that the beta related to the climate change factor is significant for 22 out of 303 companies in the sample when hedging Policy news. Secondly, we obtain the hedge portfolio time series ($h_t^{\text{I policy}}$). We also get the t-statistic to check if this time series is significantly different from zero. In this case we obtain a t-statistic of -0.023 and a p-value of 0.982. As with Emissions news innovations, we cannot reject the null hypothesis that the return of the hedge portfolio for Policy news ($h_t^{\text{I policy}}$) is equal to zero.

It is necessary to mention that Fama-MacBeth approach has some drawbacks. Firstly, this methodology requires a large number of observations over time. In our case, the amount of data available over time may be insufficient to apply this methodology effectively. In addition, this method requires knowledge of all factors in the model. In our case we have considered the climate risk factor and the three fundamental factors of Fama and French, but additional factors may be required. Finally, the procedure is not robust to measurement error in the factor of interest, for us the climate risk factor. If this factor is subject to significant measurement error it may affect the accuracy of the results obtained with this methodology.

5.2 ETFs in hedge portfolios

ETFs (Exchange Traded Funds) in hedge portfolios can be useful, because with a single trade we can track specific industries, regions or indices. We can think that there are certain sectors that are more exposed to climate change, such as the energy sector. It would also be interesting to consider ETFs related to renewable energy sources but we have not found data available for our sample period. As suggested by Engle et al. (2020), in this section we include energy ETFs returns in the mimicking portfolio approach. We are going to replace the portfolio return based on environmental scores with an ETF return. We made this decision based on the idea that news related to climate change could have a significant impact on the energy sector.

Specifically, we are going to analyze the performance of hedge portfolios using returns of the SPDR MSCI Europe Energy UCITS ETF. This hedge fund tracks the performance of large and medium-sized European companies in the energy sector according to the Global Industry Classification Standard (GICS). We obtain monthly data between January 2017 and December 2022 from Eikon Refinitiv.

We can reformulate equation 1 to include this ETF return:

$$\begin{aligned} I_t^{\text{ECCNI}} =& \xi + w_{\text{SIZE}} Z_{t-1}^{\text{SIZE}'} r_t + w_{\text{VALUE}} Z_{t-1}^{\text{VALUE}'} r_t \\ & + w_{\text{MARKET}} Z_{t-1}^{\text{MARKET}'} r_t + w_{\text{ETF}} r_t^{\text{ETF}} + e_t \end{aligned} \tag{8}$$

Below, we present the results obtained from this regression for the total index and for its five sub-categories.

Table 5: Regression: ECCNI using ETF returns.

	Total	Emissions	Fossil	Gas	Policy	Renewables
Constant	0.23374	1.21054***	0.6107	0.73295*	0.64839	0.52966
	(0.32635)	(0.34322)	(0.4065)	(0.42834)	(0.40317)	(0.35539)
$\tilde{r}_t^{SIZE}$	1.95766*	2.47585**	0.4416	1.17507	1.85901	−0.50893
	(1.05711)	(1.05711)	(1.3168)	(1.38748)	(1.30594)	(1.15116)
$\tilde{r}_t^{VALUE}$	−0.08136	0.28113	−0.1831	−0.03787	0.08715	−0.06949
	(0.25028)	(0.26322)	(0.3118)	(0.32850)	(0.30920)	(0.27255)
$\tilde{r}_t^{MARKET}$	−1.10910**	−1.29422**	−0.2511	−0.66734	−0.95871	0.27554
	(0.54660)	(0.57486)	(0.6809)	(0.71743)	(0.67527)	(0.59523)
r_t^{ETF}	0.18215**	−0.09473	0.1440	0.03381	0.07694	0.08537
	(0.08817)	(0.09273)	(0.1098)	(0.11572)	(0.10892)	(0.09601)
R-squared	0.14617	0.07469	0.03383	0.02381	0.06096	0.02893

This table shows results from equation 8 by using the SPDR MSCI Europe Energy UCITS ETF return instead of the E-scores.

Table 5 shows that, by substituting the E-scores portfolio by the return of the mentioned ETF, the results for the total index are better than in previous sections. We observe a significant and positive relationship between the EU Climate Change News Index innovations and the hedge fund return. We can also mention the considerable increase in R-squared when hedging EU Climate Change News Total Index innovations. In other words, the hedge portfolio based on ETFs might perform better than the E-score-based hedge portfolio for the total index.

In Table 5, for Emissions news we can observe a lower R-squared compared to the results obtained in previous sections. This means that most of the R-squared obtained in this category in previous sections is the result of the portfolio based on the rescaled E-scores, and not of the other portfolios (size, value and market), which are also included in equation 8.

6 Conclusions

Climate change is now recognised as a new source of financial risk. In this context, the need for investors to hedge against the effects of climate change is emerging. In our study, we test whether it is possible to hedge climate change news innovations in Europe. We try to hedge climate risk by using trading assets in the Stoxx Euro 600 Index. Our hedge targets are formed by EU Climate Change News Index innovations and its five sub-categories: Emissions, Fossil Fuels, Gas, Policy and Renewables. First of all, we try to hedge them by using the mimicking portfolio approach. In this methodology we have formed four portfolios based on different characteristics (size, value, market and E-scores) for each hedge target. The portfolio relating to the E-scores has been built in two ways, using either the demeaned absolute values or the rescaled values. Secondly, as a robustness check, we try to hedge innovations in climate change news by using the Fama-MacBeth approach. Here we have included a climate risk factor formed by climate news innovations and we have also considered the three Fama and French factors (SMB, HML and market). At the end, we have replaced the environmental scores-based portfolio return with ETFs returns related to the energy sector in the mimicking portfolio approach to see whether it improves the performance of the hedge portfolio or not.

We find evidence that the mimicking portfolio approach can be successful in hedging Emissions and Policy news innovations by using the rescaled E-scores. We can state that the E-scores are significant in hedging news innovations in these two sub-categories in Europe for the sample period considered. Emissions and Policy news can be linked to the aforementioned *transition risk*, e.g. the emergence of new measures to reduce emissions or to incentive clean energy as well as the introduction of new climate regulation or international agreements. In this context, it can be understandable that the environmental factor is significant. The resulting hedge portfolios require rebalancing based on constantly updating information on the relationship between stock returns and climate change news. The composition of the resulting hedge portfolios is based on long positions in companies with low E-scores and short positions in companies with high E-scores. It is necessary to mention that the resulting hedge portfolios do not comply with the belief that the optimal hedge of climate risks is carried out with long positions in 'clean' industries and short positions in 'dirty' industries. Specifically, we found that the *Financials* sector is important in long positions, while in short positions the *Industrials* sector stands out. In essence, we have shown that we can construct equity portfolios which hedge Emissions and Policy news innovations by using the mimicking portfolio approach. However, this is not the case for the total news index innovations. In this sense, it is worth noting that we have found evidence that hedge portfolios including ETFs returns have a higher ability to hedge EU Climate Change News Total Index innovations. Results should obviously be considered in the time span and geographical area studied.

The implications of the findings may be relevant for practitioners, in particular for sustainable investment professionals or risk managers. Through this study, we provide valuable information on how to hedge climate risk and it can be a starting point for building the hedge. This information may even be useful for policy makers to better understand climate risk hedging practices in Europe.

Based on the findings of this study, some avenues for future research can be explored. First, if we could observe longer time series of climate news measures, the described methodologies should deliver better portfolios to hedge climate change news. In addition, for further research, it would be useful to obtain monthly data of the E-scores that could improve the estimation of the hedge portfolios. Monthly data on E-scores could be obtained from databases such as Sustainalytics. Moreover, further studies could explore the impact of US news on the European market, by making use of a news index such as the one created by Engle et al. (2020). Besides, future research could consider differentiating between positive and negative climate news in Europe.

It is also necessary to consider that in this study we have used OLS as the estimation method but, if we understand hedging as a tail event, it would be interesting to extend this study by using Quantile Regression. Finally, we leave for further research to consider changes in the volatility of the EU Climate Change News Index innovations. For example, following a Switching Markov approach to consider states with different volatility in these innovations.

References

Alessi, L., Ossola, E., & Panzica, R. (2021). What greenium matters in the stock market? The role of greenhouse gas emissions and environmental disclosures. *Journal of Financial Stability*, *54*, 100869.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Ardia, D., Bluteau, K., Boudt, K., & Inghelbrecht, K. (2022). Climate Change Concerns and the Performance of Green vs. Brown Stocks. *Management Science*.

Aven, T. (2020). Climate change risk–what is it and how should it be expressed? *Journal of Risk Research*, *23*(11), 1387–1404.

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

Carney, M. (2015). Breaking the Tragedy of the Horizon – climate change and financial stability. *Bank of England*(September), 1–16. Retrieved from `www.bankofengland.co.uk/publications/Pages/speeches/default.aspx`

Cornell, B. (2021). ESG preferences, risk and return. *European Financial Management*, *27*(1), 12–19.

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

Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance*, *50*, 131–155.

Fama, E. F., & MacBeth, J. (1973). Risk , Return , and Equilibrium : Empirical Tests. *Journal of Political Economy*, *81*(3), 607–636.

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

Hartvig, Á. D., Pap, Á., & Pálos, P. (2023). EU Climate Change News Index: Forecasting EU ETS prices with online news. *Finance Research Letters*, *54*, 103720.

Huynh, T. D., & Xia, Y. (2021). Climate Change News Risk and Corporate Bond Returns. *Journal of Financial and Quantitative Analysis*, *56(6)*.

Lamont, O. A. (2001). Economic tracking portfolios. *Journal of Econometrics*, *105*(1), 161–184.

Pástor, L., Stambaugh, R. F., & Taylor, L. A. (2021). Sustainable investing in equilibrium. *Journal of Financial Economics*, *142*(2), 550–571.

Pukthuanthong, K., Roll, R., Wang, J., & Zhang, T. (2019). A new method for Factor-Mimicking Portfolios. *SSRN Electronic Journal*.

Roll, R., & Srivastava, A. (2018). Mimicking portfolios. *The Journal of Portfolio Management*, *44*, 21–35.

Stoll, H. R. (2003). Chapter 9 - market microstructure. In *Corporate finance* (Vol. 1, p. 553-604). Elsevier.

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

Zhang, Y., He, M., Liao, C., & Wang, Y. (2023). Climate risk exposure and the cross-section of Chinese stock returns. *Finance Research Letters*, *55*, 103987.