Carbon Risk Premium and Worries about Climate Change *†

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Abstract

This paper sheds light on the impact of investor worries about climate change on the pricing of emission (carbon-intensive) and clean (low-emission) stocks. We estimate the carbon risk premium in a cross-section of over 4,800 firms in 21 countries. We do not find evidence of a carbon risk premium when investor worries about climate change are low. Moreover, the carbon premium is significant for medium-high quantiles of the return distribution when investors' worries are high. Overall, our results are consistent with an interpretation that non-worried investors are not demanding compensation for their exposure to carbon emission risk.

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1 Introduction

The European Union (EU) aims to become the first climate-neutral continent by 2050. This objective is at the heart of the European Green Deal and in line with the EU's commitment to global climate action under the Paris Agreement. This paper investigates whether public attitudes towards climate change can help to achieve the EU's climate targets through the carbon pricing channel. Indeed, the evaluation and pricing of carbon risk can facilitate the climate transition by giving incentives to firms to reduce their emissions.

Prior literature linking emissions to stock returns has shown that stocks of high-emission firms tend to outperform stocks of firms with lower levels of emissions (Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023). This difference in returns cannot be explained by common risk factors and it has been attributed to carbon risk. However, recent studies have challenged this evidence (Aswani et al., 2023; Atilgan et al., 2023; Zhang, 2023). Aswani et al. (2023) argue that associations are driven by unscaled emissions estimated by the data vendor rather than emissions disclosed by firms. Moreover, emission intensity (emissions scaled by firm size) is not associated with returns. Atilgan et al. (2023) find that the carbon premium partially results from an unpriced externality. This paper contributes to the debate by exploring the role of investors' worries about climate change in explaining cross-country differences in the carbon risk premium using different definitions of emission and clean stocks. Our hypothesis is that a lower level of worry may induce investors to neglect information on firms' exposure to carbon risk and hence not price this risk. Several studies have shown that institutional and retail investors are still not fully pricing climate risks and opportunities in their portfolios (Hong et al., 2019; Alok et al., 2020; Krueger et al., 2020; Benedetti et al., 2021; Faccini et al., 2021; Ehlers et al., 2022). Moreover, emotional factors such as climate sentiment impact the stock pricing of emission and clean firms (Briere and Ramelli, 2021; Santi, 2023).

Since investor worry about climate change is a latent variable, we propose to use the answers to the questions on "Public attitudes to climate change" of the European Social Survey (ESS) Round 8 (ESS, 2016) to measure them. In particular, we employ the worry index for the regions with an exchange city as a proxy of investors' worries about climate change. Exchange cities are important cities in which investors tend to be located, and prices are affected by domestic investors (see Chan et al., 2003; Choi et al., 2020). Furthermore, regions with an exchange city tend to attract more and larger businesses, and they have different characteristics than other regions. For instance, in

Italy, the region of Milan is very different than other Italian regions. Hence, national estimates of worries about climate change may not be adequate to represent the level of worries of regions with an exchange city. Since the ESS is not designed to produce reliable estimates and analyses at the sub-national level (ESS, 2016), we employ small area estimation methods (Rao and Molina, 2015). Although the latter methods are not well-known in Finance, they are well-established in Statistics with the seminal works by Fay and Herriot (1979) and Battese et al. (1988) followed by numerous applications in many fields. Moreover, these approaches are part of the methods used in Official Statistics (see e.g., Rao and Molina, 2015).

We employ Refinitiv Eikon Datastream to retrieve data on adjusted closing prices, market capitalization, and other company information. We consider stocks traded in 26 stock exchanges located in 21 European countries. We use stocks' cumulative returns in 2016, while firms' characteristics refer to the fiscal year 2015. Consistent with previous research (e.g., Choi et al., 2020), we identify a stock as an emission (carbon-intensive) stock if it belongs to one of the five industry sectors classified as major emission sources by the Intergovernmental Panel on Climate Change (IPCC). The remaining stocks are classified as clean (low-emission) stocks. Alternatively, we use scope 1 and scope 2 total CO_2 equivalent emissions and emission intensity (total CO_2 equivalent emissions scaled by total revenue). Carbon emission data are from Refinitiv ESG. Since the difference in returns of emission and clean stocks may be due to several factors, we control for market-to-book ratio, market capitalization, capital expenditure, Return On Assets (ROA), asset growth, and exchange city fixed effect. We augment this data with country-level variables from the World Bank, OECD, and Germanwatch. We consider variables of economic development, country energy structure, environmental policies, and exposure to climate physical risk.

We show that worries about climate change are higher in less economically developed areas and areas more dependent on non-renewable sources for electricity production. We do not find evidence of worries about climate change being dependent on the stringency of environmental policies and exposure to climate physical risk. Furthermore, on average worries about climate change are significantly different in regions with an exchange city than in other regions suggesting that using country-level estimates of worry about climate change as a proxy of investors' worries could introduce noise.

Importantly, we show that the difference in returns of emission and clean stocks depends on investors' worries about climate change. First, we classify European regions with an exchange city as little worried, and worried. Then, we investigate the difference in returns of emission and clean stocks in the whole sample, little worried and worried regions using a plethora of statistical methods. Consistent with Hsu et al. (2023) and Bolton and Kacperczyk (2021), we find that emission stocks have significantly higher returns than clean stocks in the whole sample when we use the IPCC definitions to identify emission stocks, moreover stock returns are positively associated with emission levels but not emission intensity. More importantly, we find a significant difference in the returns of emissions and clean stocks only when investors are worried about climate change. Indeed, the carbon risk premium is not significant when investors show a low level of worry about this issue. This evidence is confirmed using the IPCC definition and emission levels.

We present additional evidence using matching techniques, which allow us to estimate the difference in returns of emission and clean stocks with similar characteristics. The average treatment effect analysis confirms the findings from the OLS regression. In order to rule out that worries about climate change might be proxying for some economic measures, we compute the average treatment effect of being an emission firm on returns for countries with high/low economic development and high/low dependence on renewable energy sources. We find that the carbon risk premium is significant in all subsamples which implies that the worry index is not proxying for economic measures. To gain further insights, we also estimate the quantile treatment effect (Firpo, 2007) which allows us to study the carbon risk premium along the distribution of returns of emission and clean firms with similar characteristics. We document that the carbon premium is significant only for medium-high quantiles when investors worry about climate change. This finding is consistent with investors paying more attention to high-return stocks and neglecting information on the environmental impact of firms reporting low stock returns hence not pricing their carbon risk. In contrast, the difference in return of emission and clean stocks is not significant when investors show a low level of worry about climate change.

To summarize, this study sheds light on the importance of investors' worries about climate change in pricing high/low emission stocks. Our findings suggest that investors only a little worried about climate change should direct greater attention to firms' emissions and that emissions can be a useful input for firm valuation. Furthermore, investors overlook information on the exposure to climate risk of low-return stocks independently of their level of worry as these stocks tend to attract low analyst coverage and attention. Overall, our results suggest that government intervention is needed to support the climate transition as market forces alone are not enough to fully price carbon transition risk.

This paper contributes to the fast-growing literature on Climate Finance. First, we add to the cross-country evidence on the relationship between emissions and stocks returns. Bolton and Kacperczyk (2023) analyse the carbon risk premium in a cross-section of 14,400 firms in 77 countries. They show that the carbon risk premia related to emissions growth, which can be interpreted as short-run exposure to transition risk, are greater for firms located in countries with lower economic development, larger energy sectors, and less inclusive political systems. Premia related to emission levels, which can be interpreted as exposure to long-run transition risk, are higher in countries with stricter domestic climate policies. The authors also argue that the premia have increased with investor awareness about climate change risk as they find evidence of higher carbon risk premiums, especially in Asia, following the signature of the Paris Agreement. Also related to our paper is the study by Karolyi et al. (2023) who consider a total of 21,902 firms from 96 countries. The authors find evidence of a so-called greenium—negative carbon risk premium—around the world. They show that the equity greenium effect is more prominent in North America and during the period before 2016. Moreover, most of the equity greenium performance cannot be explained by exposures to return factors prominent in the asset pricing literature. Our contribution differs from the above two studies as we focus on the importance of investors' worry about climate change for the pricing of carbon risk. Moreover, we do not limit our analysis to the study of the average effect but we explore the relationship between climate worries and stock returns along the quantiles of the return distribution. The paper is also related to the country-level literature on carbon risk. Bolton and Kacperczyk (2021) find that stocks of firms with higher total CO_2 emissions earn higher returns, controlling for size, book-to-market, and other return predictors. These results are consistent with investors demanding compensation for their exposure to carbon risk. Hsu et al. (2023) study the effects of environmental pollution on the cross-section of stock returns. They find that highly polluting firms are more exposed to environmental regulation risk and demand higher average returns. Engle et al. (2020) propose and implement a procedure to dynamically hedge risk with respect to climate change news.

A limitation of our analysis is that, in the ESS, questions on "Public attitudes to climate change" are available only in round 8. Thus, our survey data do not allow us to study the evolution over time of the link between investors' worry about climate change and the carbon risk premium. However, public attitudes toward climate change tend to be persistent over time. We have analysed the answers to the question "How worried are you about climate change?" which was repeated also in round 10 of the ESS and we do not observe large differences in the level of worry of Europeans. In Appendix C, we present a paired bar plot of the proportions of Europeans at least somewhat worried about climate change in 2016 and 2020. We can observe that in almost all countries the proportion of worried respondents has increased, although the increase is generally small. On the other hand, an advantage of our survey data is that they allow us to address the heterogeneous spatial distribution of public attitudes toward climate change in Europe. Recent studies perform textual analyses of newspaper articles to measure concerns about climate change (Engle et al., 2020; Ardia et al., 2022). However, data from national newspapers do not allow spatial comparisons at the regional level. Indeed, the 26 regions included in our sample speak 18 different languages, which makes textual analysis of newspaper articles unfeasible. For this reason, the great majority of studies using news media data focus on English-written articles most of them on the U.S. Furthermore, although news coverage is undoubtedly an important determinant of public attitudes, several other aspects such as culture, education, and social influence are crucial as well. Opinions expressed through surveys are the result of all these aspects, thus, they can better describe public attitudes towards a certain topic. To the best of our knowledge, our study is the first one to provide evidence of the differences among European regions concerning the link between the carbon risk premium and worries about climate change.

The remainder of this article is structured as follows. Section 2 describes the data and variables used in the analysis. Section 3 presents the methodology used to estimate the worry index at the regional level and it discusses the estimates. Section 4 presents the methods and the results of the analysis of the difference in returns of emission and clean stocks. Section 5 discusses the empirical findings. Section 6 presents the conclusions.

2 Data description

In this section, we describe the data sources employed, as well as the main variables used in our analysis.

2.1 Worry about climate change

The variables used to construct the indicator of worries about climate change are from the European Social Survey (ESS) round 8 (ESS, 2016). ESS is a nationally representative European cross-national sample survey that has been running since 2001 bi-annually. The ESS is especially valuable for its high-quality sampling and data collection, coverage of European countries, and broad suite of questions on climate change.[1] The ESS questionnaire consists of a core section and a rotating section. The core section focuses on a range of different themes that are largely repeated in each round. The rotating section is dedicated to specific themes, which are sometimes repeated in later rounds of the ESS. We employ ESS round 8 because it is the only round where data on the topic "Public attitudes to climate change" is collected. We focus on nine ESS items included in round 8 (Poortinga et al., 2018). The questions used are phrased in the questionnaire as follows:

1. How worried are you about climate change?
2. How worried are you that there may be power cuts in [country]?
3. How worried are you that energy may be too expensive for many people in [country]?
4. How worried are you about [country] being too dependent on energy imports from other countries?
5. How worried are you about [country] being too dependent on using energy generated by fossil fuels such as oil, gas and coal?
6. How worried are you that energy supplies could be interrupted by natural disasters or extreme weather?
7. How worried are you that energy supplies could be interrupted? ...and by insufficient power being generated?
8. How worried are you that energy supplies could be interrupted? ...and by technical failures?
9. And how worried are you that energy supplies could be interrupted by terrorist attacks?

Responses are given on the following scale: not at all worried (1), not very worried (2), somewhat worried (3), very worried (4), and extremely worried (5). We employ the answers to the above questions to develop a regional indicator of worries about climate

[1]The countries included in the ESS round 8 are Austria, Belgium, Czechia, Estonia, Finland, France, Germany, Hungary, Iceland, Ireland, Israel, Italy, Lithuania, Netherlands, Norway, Poland, Portugal, Russian Federation, Slovenia, Spain, Sweden, Switzerland, and the United Kingdom. We exclude from our analysis Israel and the Russian Federation.

change, and we use the level of worries of regions with an exchange city as a proxy of investor worries about climate change.

Given the above questions, the indicator of worries about climate change captures mainly worries concerning the climate transition which is consistent with our objective to study the carbon risk premium in the European stock markets.

Furthermore, we would like to stress the difference between worry and awareness. More than 90% of Europeans recognize that the world's climate is at least probably changing (Poortinga et al., 2018). Moreover, the great majority of Europeans recognize that climate change is at least partly caused by human activity and that the consequences will be bad (Poortinga et al., 2018). However, despite being aware of climate change, just over a quarter of the respondents report being very or extremely worried about climate change which is relatively low (Poortinga et al., 2018). Hence, worries about climate change are distinct from awareness.

2.2 Clean and emission stocks

We employ Refinitiv Eikon Datastream to retrieve data on adjusted closing prices. We consider stocks traded in several European financial markets, in each market we focus on primary quotes.[2] Since the literature points out that Datastream may suffer from data errors, similarly to Hou et al. (2011), Ince and Porter (2006), and others we remove all monthly returns that are above 300% and reversed within a month. We also remove zero monthly returns (Datastream repeats the last valid data point for delisted firms). Then, we winsorize raw returns at the top and bottom 1% in each exchange in each month.[3] For each stock, we compute the cumulative returns of the year 2016, and we remove stocks with missing observations in that year.

We identify emission and clean stocks in two ways. The first method involves using the industry in which the firm operates. The IPCC has identified the industry sectors - Energy, Transport, Buildings, Industry, and Agriculture, Forestry, and Other Land Use (AFOLU) - as major emission sources.[4] We manually match the Datastream level

[2] We include stocks quoted in the Berliner Börse, Bolsa de Madrid, Borsa Italiana, Börse Düsseldorf, Börse München, Börse Stuttgart, Budapest Stock Exchange, Deutsche Börse AG, Euronext, Hamburg Stock Exchange, Helsinki Stock Exchange, Ljubljana Stock Exchange, London Stock Exchange, Mercado Continuo Espanol, NASDAQ OMX, Oslo Bors, Prague Stocks Exchange, SIX Swiss Exchange, Vienna Stock Exchange, Vilnius Stock Exchange, and Warsaw Stock Exchange.

[3] As a robustness test, we performed the analysis using winsorization at the top and bottom 2.5% and 5%. Results are available upon request and they confirm the main findings of the paper.

[4] See Krey et al. (2014) for a full list of sectors subcategories.

6 industrial classification codes with the IPCC category codes.[5] Following Choi et al. (2020), we classify all firms in the matched industries as emission (carbon-intensive) firms, the rest is classified as clean (low-emission) firms. Our data includes a total of 4,886 stocks: 3,876 clean stocks and 1,010 emission stocks.

The second method involves using carbon emission data from Refinitiv ESG. We use scope 1 and scope 2 total CO_2 equivalent emissions and emission intensity. Emission intensity is computed as the ratio of scope 1 and scope 2 total CO_2 equivalent emissions and total revenues. Refinitiv ESG follows greenhouse gas (GHG) protocol for all their emission classifications by type. Consistent with the literature, we winsorize emission data at 2.5% level (Bolton and Kacperczyk, 2021, 2023).

Throughout the paper, we primarily use IPCC definitions because they are available for all firms. Using emission data, the sample size reduces to 616 observations against 4,886 when we use IPCC definitions. Moreover, data from Refinitiv ESG may have a selection issue and the results should be interpreted with caution.

2.3 Control variables

We employ Refinitiv Eikon Datastream to retrieve data on firms' characteristics. Market-to-Book (MTB) is defined as the market value of the ordinary (common) equity divided by the balance sheet value of the ordinary (common) equity in the company. Market capitalization (MktCap) is the product of the closing price of the company's stock at their fiscal year-end and the common shares outstanding. Capital expenditure per share (CapExp) represents capital expenditure for the 12 months ended the last fiscal year divided by common shares outstanding. Return on assets (ROA) is the percentage return on average of last year's and current year's total assets. Asset growth (AssetGR) is the 1-year annual percentage growth of total assets. We winsorise all variables at the 1% and 99% levels in each exchange to reduce the influence of outliers (Beaver and Ryan, 2000).

Table 1 reports the average values of the cumulative returns, market-to-book ratio (MTB), market capitalization, capital expenditure per share, return on assets (ROA), and asset growth. These values are reported per country and per emission and clean stocks. We can observe that for most of the countries on average emission stocks generate higher returns, and have a larger size than clean stocks. The market-to-book ratio is generally greater than 1 on average for both emission and clean stocks in all the countries.

[5] Appendix A contains a list of Datastream level 6 industrial classification codes (INDG) available from Refinitiv Eikon Datastream and the matching IPCC category codes which are classified as carbon intensive.

Moreover, for most of countries, the average market-to-book ratio of emission firms is lower than that of clean firms. A high market-to-book ratio might mean that the market is overvaluing the company's equity. Emission stocks report a higher capital expenditure per share than clean stocks for the majority of countries. Instead, the asset growth of emission stocks is lower than the asset growth of clean stocks for the majority of countries. We do not observe any tendency concerning the return on assets of emission stocks as compared to clean stocks.

Table 1: Summary Statistics

Countries	Returns	MTB	Market Cap (€ Mil.)	Cap. Exp. per share (€)	ROA (%)	Asset Growth (%)
Austria						
Emission	0.1497	1.8734	1.5657	3.9231	3.2263	0.1344
Clean	0.0167	1.1429	1.8069	3.5652	4.6041	94.8493
Belgium						
Emission	0.1062	2.4491	1.7251	4.5076	4.1989	13.2046
Clean	0.0620	3.0146	2.2020	2.5133	0.4123	23.1136
Czechia						
Emission	0.0635	1.5488	2.7569	4.2666	11.2500	9.1638
Clean	0.0109	2.4600	3.2239	0.1952	8.5438	-21.5684
Estonia						
Emission	0.6548	1.4100	0.0981	0.0232	10.2948	-17.7659
Clean	0.0427	0.7730	0.0079	0.0320	3.6406	-9.4898
Finland						
Emission	0.2540	2.2233	2.1997	0.6243	4.9119	4.9544
Clean	0.0952	2.7785	1.8363	0.3586	9.2969	11.9574
France						
Emission	0.1896	1.5215	4.5561	4.4141	0.8474	7.8647
Clean	0.0812	2.1424	3.3324	2.4795	-1.8850	25.7168
Germany						
Emission	0.0823	2.0193	5.0048	3.3618	1.5527	6.6445
Clean	0.0800	2.3788	2.5488	1.3098	1.0550	16.7142
Hungary						
Emission	0.2743	1.0850	0.7161	2.2812	1.7751	-2.8420
Clean	0.3427	1.4294	0.8611	0.3661	2.9877	5.2084
Iceland						
Emission	-0.1000	1.7925	0.8038	0.0662	9.5307	3.8840
Clean	0.2857	1.3166	0.1790	0.0113	7.8274	4.2117
Ireland						
Emission	-0.0791	3.1544	3.4807	0.3061	4.2322	12.6442
Clean	0.1151	5.3385	2.4339	0.3117	6.5502	23.7583
Italy						
Emission	-0.0549	2.1620	2.9318	0.4976	2.2165	3.3758
Clean	-0.1370	2.4945	1.7861	0.2990	0.8986	12.9260
Lithuania						
Emission	0.2727	0.6937	0.0342	0.3208	2.8318	9.4950
Clean	0.1902	4.1714	0.0307	0.0769	6.9646	0.2836

(continued)

continued

Countries	Returns	MTB	Market Cap (€ Mil.)	Cap. Exp. per share (€)	ROA (%)	Asset Growth (%)
Netherlands						
Emission	0.1518	2.9630	2.6526	1.3171	4.8154	3.6167
Clean	0.0330	3.3952	8.6950	1.5774	3.2640	16.8644
Norway						
Emission	0.1953	1.5744	1.1107	10.6418	-5.0817	18.7555
Clean	0.2789	2.0668	1.3622	1.4088	-3.5961	20.5091
Poland						
Emission	0.1528	1.3251	0.3612	0.7260	1.4018	6.9498
Clean	0.0759	1.9693	0.3148	0.3098	1.9975	19.9323
Portugal						
Emission	-0.1487	1.7962	0.6542	0.3057	2.9286	-4.3628
Clean	-0.0516	6.2223	1.9544	0.2556	4.1786	3.3733
Slovenia						
Emission	0.1787	1.1150	0.4247	10.0007	6.6900	-0.8750
Clean	0.1451	0.8439	0.4652	5.1919	3.4881	3.1457
Spain						
Emission	0.2460	2.9749	5.4622	0.7149	3.5194	2.4191
Clean	0.0481	3.3543	5.5554	0.6158	3.2647	15.9734
Sweden						
Emission	0.1253	5.8212	2.2667	0.3289	-7.1030	4.2294
Clean	0.1267	3.9538	1.7922	0.2566	-4.5527	31.5995
Switzerland						
Emission	0.1520	3.3865	8.4014	28.7532	3.9444	0.3922
Clean	0.0754	2.9804	8.7387	7.5849	1.9202	6.0540
United Kingdom						
Emission	0.2953	3.3295	5.2566	0.5542	-6.1107	10.1114
Clean	0.0347	3.7844	3.4869	0.2223	-1.6055	31.4095

Notes: The table reports the average values of the cumulative returns, market-to-book ratio (MTB), market capitalization, capital expenditure per share, return on assets (ROA), and asset growth. Cumulative returns refer to 2016, the remaining variables refer to 2015. We use the IPCC definitions to identify emission and clean stocks.

We augment this data with country-level variables from the World Bank, OECD, and Germanwatch. We consider variables of economic development such as a country's health expenditures per capita in current dollars in a given year (HLTH) and the percentage of a country's GDP that is produced in a given year in the manufacturing sector (MANUF).[6] We also include variables on the country's energy structure. In particular, we use the ratio between energy supply and gross domestic product measured at purchasing power parity in a given country (ENINT) and a country's share of electricity generated by renewable power plants in total electricity generated by all types of plants in a given year (ELRENEW). Moreover, we employ the OECD environmental policy stringency index (EPS), and the Germanwatch global climate risk index (GCRI).

[6] We do not consider GDP per capita as it is highly correlated with the other variables.

3 Investors' worry about climate change

Worries about climate change are a latent multidimensional phenomenon. This means that their measurement requires considering multiple dimensions such as worries about the use of fossil fuels, interruptions in energy supply, price of energy, and other related issues (Whitmarsh, 2011). As mentioned in the previous section, we propose to use the answers to the questions on "Public attitudes to climate change" of the European Social Survey (ESS) Round 8 (ESS, 2016) since the survey uses high-quality sampling and data collection methods, it has good coverage of European countries and a broad suite of questions on climate change.

However, the ESS targets the general population while we want to measure investors' worries about climate change in order to then study their influence on the pricing of emission and clean stocks. We propose to use the worry index for the regions with an exchange city as a proxy of investors' worries about climate change. Indeed, investors tend to be located in exchange cities and their surroundings (see Chan et al., 2003; Choi et al., 2020). Furthermore, regions with an exchange city tend to attract more and larger businesses, and they have different characteristics than other regions. Moreover, Moretti and Whitworth (2020) show that public attitudes are spatially heterogeneous at small geographical scales in Europe. However, regional sample sizes of the ESS are relatively small given that the primary purpose of the survey design is to allow comparative analyses across European countries only. Therefore, we use small area estimation methods to produce reliable estimates at the regional level (Moretti and Whitworth, 2020).

In what follows, we discuss small-area estimation methods used to produce the regional indicator of worries about climate change as well as its estimates.

3.1 Small area estimation

Because of the growing need for detailed spatial information, small-area estimation is a group of statistical approaches increasingly in demand from researchers and policy-makers. Furthermore, small area estimation methods involve lower costs than collecting sufficiently large sample data to produce reliable direct estimates[7] for smaller geographies (Moretti and Whitworth, 2020).

Small area estimation methods are always based on two key steps: i) estimation of

[7]In survey statistics, direct estimates refer to estimates that are obtained using only sample information, as opposed to indirect estimates that use auxiliary information to improve the estimates obtained on the sample.

the relationships between explanatory variables and target outcome variables in a sample survey; ii) application of those relationships to the same set of explanatory variables at the small area level (usually from the Census of administrative data). The output is a new small area estimate for the indicator of interest.[8]

In this paper, we consider a two-step approach following Moretti et al. (2019).[9] First, we create a latent variable measuring worries about climate change at the respondent level using a factor analysis model for categorical variables. This is carried out by estimating the factor scores based on the estimated factor analysis model parameters (Hershberger, 2014; Kaplan, 2008). Second, we adopt an area-level small area estimation approach (Rao and Molina, 2015) to provide precise and accurate estimates of the worry indicator for European regions.[10] In particular, we use the so-called Empirical Best Linear Unbiased Predictor (EBLUP) which combines direct estimates based on the Horvitz-Thompson estimator (Horvitz and Thompson, 1952) with synthetic estimates based on the well-established Fay-Herriot model (Fay and Herriot, 1979). The Fay-Herriot model avails of area-level auxiliary variables. The two estimators are combined according to a weighting factor (the shrinkage factor) dependent upon the variance of the direct estimator. Specifically, more weight is given to the direct estimate when its variability is small (large regional sample size), conversely, more weight is attached to the synthetic component when the variability of the direct estimate is large (Fay and Herriot, 1979; Rao and Molina, 2015). In this way, we optimise the final estimates in terms of the minimisation of their bias and variance (mean squared error) when compared to either the direct or synthetic estimators separately. In fact, whilst the direct estimates are unbiased, they show large variances for those regions with small sample sizes. Regarding the methods to estimate the measures of reliability for the direct estimates (Coefficient of Variation) and EBLUPs (Relative Root Mean Squared Error), we refer to Särndal et al. (2003) and Moretti et al. (2019), respectively.

The auxiliary variables used to produce the small area estimates are retrieved from the Eurostat Regional Statistics database.[11] The regional variables used include proportions of citizens in the following age groups: 15-29, 30-49, 50-64, 65-84, and over 85, proportions of males, GDP per capita, the proportion of married citizens, the proportion of citizens with primary and lower secondary education qualification, and the proportion of citizens

[8]We refer to Rao and Molina (2015) for a review of the literature on small area estimation methods.

[9]We refer to Moretti et al. (2019) for technical details.

[10]The regions in the European Social Survey are geographical areas at the level NUTS (Nomenclature of Territorial Units for Statistics) 2 (or below).

[11]See website: https://ec.europa.eu/eurostat/web/regions/data/database.

with tertiary education qualification. These variables show a high spatial variation across European regions and they are widely used in small area estimation of public attitudes and social indicators (see Moretti and Whitworth, 2020; Moretti et al., 2019). Furthermore, our small area models perform well using these variables. In Appendix B, we report extensive diagnostic tests to evaluate the small area estimates.

For comparability reasons, we rescale the regional estimates between 0 and 1 using the 'min-max' criterion (Commission et al., 2008; Moretti and Whitworth, 2020).

3.2 Regional estimates of worry about climate change

We show in Figure 1 a map of the indicator of worry about climate change for all the European regions (with and without an exchange market).[12] For completeness, we also add the exchange cities to the map. Notice that we locate Iceland and the Canary Islands close to the mainland in order to produce a smaller map.

We can observe an evident heterogeneity of the estimates of the worry indicator between regions. In general, Europeans do not show a very high level of worry about climate change. Citizens of France, Belgium, and Finland are the most worried about climate change. In France, the northern regions together with Centre Val de Loire, and the southern region of Provence show a particularly high level of worry. This can be also observed in the Spanish regions located on the Mediterranean coast. It is interesting to observe the difference in worries about climate change in the Nordic countries. Nordic countries with the exception of Finland do not show a high level of worries about climate change. We believe that this difference is due to the higher dependence of Finland on fossil fuels. In 2016, Finland reported that 58.60% of its energy came from fossil fuels (Ritchie and Roser, 2020). This percentage was 33.05% in Sweden, and 30.78% in Norway (Ritchie and Roser, 2020). Overall, the level of worries in Norway does not show any regional differences while there are only small regional differences in Sweden and Finland. Differently, eastern European countries are characterised by a large between-region variability. Low values of the worry indicator can be observed also in Iceland, Switzerland, some eastern European regions, and the West/North-Western Irish regions.

To get further insights into the determinants of the level of worry about climate change, we estimate the following regression:

[12] The small area estimation diagnostics outputs are reported in Appendix B.

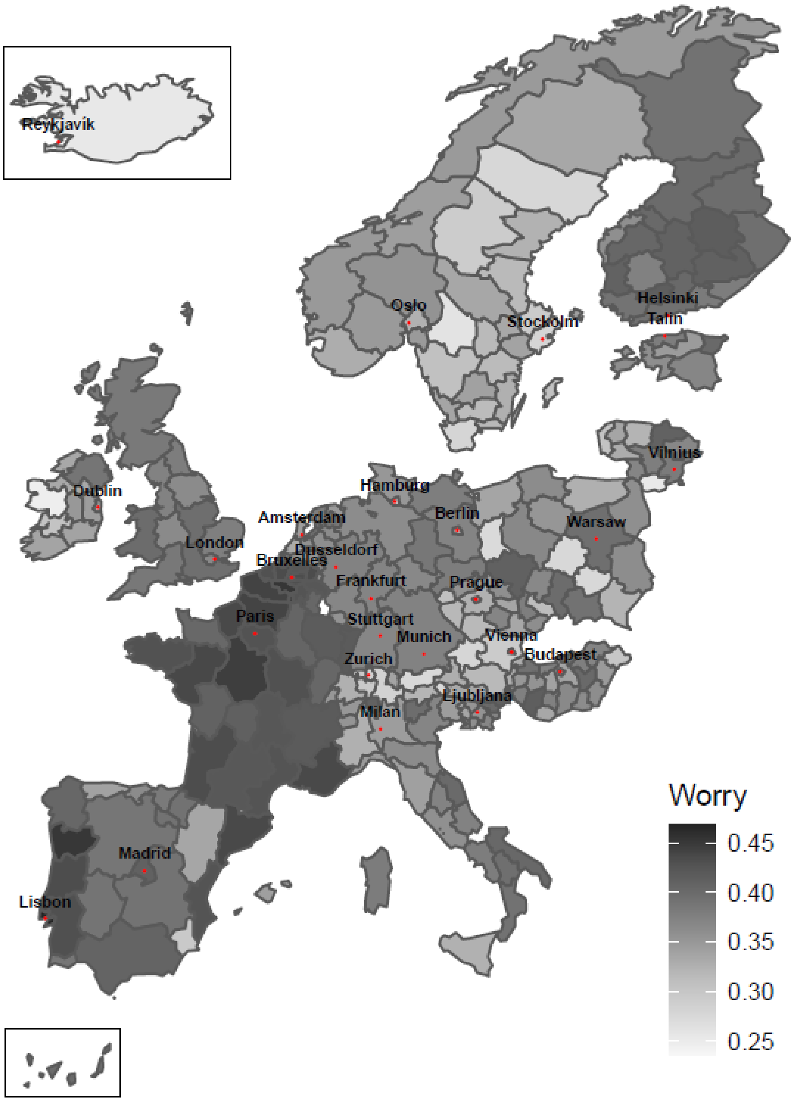

Figure 1: Map of worry about climate change in European regions.

Notes: The figure displays a map of the indicator of worry about climate change for all European regions. The regional indicator has been estimated with small area estimation techniques from the questions of the ESS round 8 listed in Section 2.1. For completeness, we also add the exchange cities to the map. Notice that we locate Iceland and the Canary Islands close to the mainland in order to produce a smaller map. The indicator of worry ranges between 0 and 1. Darker colours denote higher levels of worry.

$$\begin{aligned} Worry_{c,r,t} = &\alpha + \beta_1 HLTH_{c,t-1} + \beta_2 MANUF_{c,t-1} + \beta_3 ENINT_{c,t-1} + \\ &\beta_4 ELRENEW_{c,t-1} + \beta_5 EPS_{c,t-1} + \beta_6 GCRI_{c,t-1} + \gamma_e + \epsilon_{c,r,t}, \end{aligned} \tag{1}$$

where $Worry_{c,r,t}$ is worry about climate change in region r of country c in year $t =$ 2016. We denote with $HLTH$ a country's health expenditures per capita in current dollars

Table 2: Determinants of worries about climate change

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.433***	0.434***	0.393***	0.385***	0.380***	0.371***	0.440***	0.428***
	(0.021)	(0.022)	(0.022)	(0.025)	(0.065)	(0.067)	(0.059)	(0.058)
HLTH	−0.001*	−0.001					0.000	0.000
	(0.000)	(0.000)					(0.000)	(0.000)
MANUF	−0.309***	−0.324***					−0.323***	−0.314***
	(0.103)	(0.107)					(0.121)	(0.120)
ENINT			−0.039	0.147			0.920	0.978
			(0.536)	(0.615)			(0.910)	(0.914)
ELRENEW			−0.078**	−0.073**			−0.089**	−0.094**
			(0.032)	(0.035)			(0.035)	(0.037)
EPS					0.136	0.407	−0.406	−0.200
					(1.589)	(1.619)	(1.019)	(1.058)
GCRI					−0.023	−0.023	−0.020	−0.020
					(0.036)	(0.037)	(0.030)	(0.031)
Exchange city FE	No	Yes	No	Yes	No	Yes	No	Yes
R^2	0.144	0.200	0.144	0.176	0.017	0.030	0.327	0.336
Observations	265	265	265	265	248	248	248	248

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table reports the estimates of Eq. (1). Standard errors are clustered per exchange city. HLTH is a country's health expenditures per capita in current dollars in a given year; MANUF is the percentage of a country's GDP that is produced in a given year in manufacturing sector; ENINT is the ratio between energy supply and gross domestic product measured at purchasing power parity in a given country. Energy intensity is an indication of how much energy is used to produce one unit of economic output in a given year. ELRENEW measures a country's share of electricity generated by renewable power plants in total electricity generated by all types of plants in a given year; EPS is the environmental policy stringency index; GCRI is the global climate risk index. Higher values should be interpreted as a lower exposure to climate physical risk.

in a given year, $MANUF$ is the percentage of a country's GDP that is produced in a given year in the manufacturing sector, $ENINT$ is the ratio between energy supply and gross domestic product measured at purchasing power parity in a given country, $ELRENEW$ is a country's share of electricity generated by renewable power plants in total electricity generated by all types of plants in a given year, EPS is the OECD environmental policy stringency index, and $GCRI$ is the global climate risk index. Higher values of $GCRI$ should be interpreted as lower exposure to climate physical risk. γ_e is the exchange city fixed effect.

In Table 2, we report the estimates of Eq. (1). We observe that worries about climate change tend to be higher when $MANUF$ and $ELRENEW$ are lower. Overall, worries about climate change are higher in less economically developed areas and areas more dependent on non-renewable sources for electricity production. We do not find evidence of worries about climate change being dependent on the stringency of environmental policies and exposure to climate physical risk.

We report in Table 3 the estimates of investors' worry about climate change in the regions with an exchange market. In Table 11 in Appendix C, we test the difference

Table 3: Investors Worries about Climate Change

Country	Exchange City	Estimate	Country	Exchange City	Estimate
Austria	**Vienna**	**0.328**	**Iceland**	**Reykjavík**	**0.236**
Belgium	Bruxelles	0.417	**Ireland**	**Dublin**	**0.333**
Czechia	**Prague**	**0.336**	**Italy**	**Milan**	**0.345**
Estonia	Talin	0.379	Lithuania	Vilnius	0.382
Finland	Helsinki	0.393	**Netherlands**	**Amsterdam**	**0.344**
France	Paris	0.429	**Norway**	**Oslo**	**0.325**
Germany	**Hamburg**	**0.314**	Poland	Warsaw	0.396
Germany	**Berlin**	**0.333**	Portugal	Lisbon	0.468
Germany	Stuttgart	0.369	Slovenia	Ljubljana	0.356
Germany	Frankfurt	0.372	Spain	Madrid	0.412
Germany	Dusseldorf	0.374	**Sweden**	**Stockholm**	**0.280**
Germany	Munich	0.374	**Switzerland**	**Zurich**	**0.287**
Hungary	Budapest	0.373	United Kingdom	London	0.366

Notes: This table shows the regional estimates obtained by the EBLUP approach under Fay-Herriot model for the regions with a stock-exchange market in it. We report in bold characters the regions classified as a little worried.

of the worry indicator in regions with and without an exchange city. The two-sample Fligner-Policello (FP) robust rank order test (Fligner and Policello, 1981) fails to accept the null hypothesis that the level of worries about climate change is the same in regions with and without an exchange city. In particular, regions with an exchange city show a significantly lower level of worry about climate change than the other regions. We identify regions with a worry index less or equal to 0.349 as little worried, between 0.350 and 0.649 as worried, and greater or equal to 0.650 as very worried.

Among the regions in Table 3, the highest value of worries about climate change is reported for the region where Lisbon is located (value equal to 0.468). This result is not surprising as Portugal has been identified as the most vulnerable country to climate change in Europe (TNP/Lusa, 2021). Higher levels of worry can be also found in the regions of Bruxelles, Paris, and Madrid. Whereas the region with the smallest level of worry is the Icelander region where Reykjavík is located (value equal to 0.236). In Iceland, about 85% of the total primary energy supply comes from renewable energy sources produced domestically. Furthermore, in 2016 the share of fossil fuels was only 15%. Interestingly, in 2015 renewable energy provided almost 100% of electricity production (Government of Iceland, 2021). Hence, the low dependence on fossil fuels for energy supply explains the low level of worries about climate change in that area. A low level of worry can be also observed in the regions of Stockholm and Zurich.

Table 4: Two-sample Fligner Policello Robust Rank Order Test

	Observations	Mean	St. Dev.	Statistic	2-tailed p-value
Panel A: All sample					
Emission	1010	0.1683	0.6756	-2.1396	0.0324
Clean	3876	0.0724	0.3883		
Panel B: Little worried					
Emission	293	0.0268	0.3438	-0.9026	0.3667
Clean	1044	0.0745	0.4352		
Panel C: Worried					
Emission	717	0.1188	0.5619	-1.9913	0.0465
Clean	2832	0.0989	0.4579		

Notes: The table presents the results of the two-sample Fligner-Policello robust rank order test on the returns of emission and clean stocks. Emission and clean stocks are identified using the IPCC definitions. In Panel A, we report the results for the whole sample. Panel B reports the results for exchange markets located in regions only a little worried about climate change, and Panel C reports the results for exchange markets located in worried regions.

4 Stock pricing and worries about climate change

In this section, we present the results of the study on the carbon risk premium when investors have different levels of worry about climate change.

We start exploring the difference in returns of emission and clean stocks by performing a two-sample Fligner-Policello (FP) robust rank order test (Fligner and Policello, 1981) to check if returns of emission and clean stocks are sampled from the same population. This test assumes that the groups of emission and clean stocks are independent samples from continuous distributions symmetric with respect to the population medians. The FP robust rank order test is performed for the entire sample, for the little worried regions, and for the worried regions. We identify a region as a little worried if it has a worry index lower than 0.35.[13] Table 4 shows that the underlying sample distribution of returns of emission stocks is not the same as the one for clean stocks. Specifically, the test indicates that emission stocks stochastically dominate clean stocks. Similar conclusions are obtained when we consider only markets worried about climate change. Differently, we find that the distribution of returns of emission and clean stocks is not significantly different when investors are only a little worried about climate change.

[13]We perform the analysis with different thresholds of the worry index to identify little worried regions and results are qualitatively the same.

4.1 Regression analysis

After testing for whether emission and clean stocks can have different distributions of returns, we analyse the return differentials of emission and clean stocks using regression analysis. We estimate the following model using OLS with clustered standard errors for the exchange city:

$$r_{i,t} = \alpha + \beta\, Emission_{i,t} + \gamma\, Controls_{i,t-1} + \epsilon_{i,t}, \tag{2}$$

where the dependent variable r is the cumulative return of stock i in 2016. $Emission$ is a dummy variable that is equal to one if firm i in 2016 is carbon-intensive. Control variables include market-to-book ratio (MTB), market capitalization ($MktCap$), capital expenditure per share ($CapExp$), return on assets (ROA), asset growth ($AssetGr$). We also control for country characteristics and we include exchange city fixed effect to control for omitted variable bias due to unobserved heterogeneity.

In Table 5, we show the OLS estimates of Eq. (2) for the whole sample in columns 1-2, little worried regions in columns 3-4, and worried regions in columns 5-6. The dummy variable $Emission$ is equal to one if the firm i in 2016 belongs to an industry classified as carbon-intensive according to IPCC and zero otherwise. First of all, we can observe that emission stocks have significantly higher returns than clean stocks. In particular, emission stocks have on average cumulative returns 8 percentage points higher than clean stocks. When investors are worried about climate change, we find that the difference in cumulative returns of emission and clean stocks is around 10 percentage points. However, when investors are only a little worried about climate change, we show that cumulative returns of emission and clean stocks are not significantly different. The results also suggest that MTB and size coefficients are broadly in line with previous contributions which find that value and smaller stocks have higher returns than growth and large stocks (Fama and French, 1993, 2015). The coefficients of capital expenditure and ROA are not significant, and asset growth is associated with significantly higher (lower) returns in little worried (worried) regions. The inclusion of country-level controls does not affect the sign and significance of our variable of interest, $Emission$.

In Table 6, we report the OLS estimates of Eq. (2) using alternative definitions of emission firms. In Panel A, we use a firm scope 1 and 2 total CO_2 equivalent emissions. In Panel B, we use a firm emission intensity. Consistent with the results obtained using the IPCC definition of emission firms, we find that returns are positively associated with emission levels in the whole sample and when we consider only worried regions. In little

Table 5: Returns of emission and clean stocks

	All sample		Little worried		Worried	
	(1)	(2)	(3)	(4)	(5)	(6)
Emission	0.080**	0.080**	0.023	0.028	0.104**	0.102**
	(0.038)	(0.039)	(0.025)	(0.026)	(0.047)	(0.048)
MTB	−0.004***	−0.004***	−0.004*	−0.004*	−0.004**	−0.004**
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Log(1 + MktCap)	−0.037***	−0.037***	−0.024*	−0.023	−0.043***	−0.043***
	(0.010)	(0.010)	(0.014)	(0.014)	(0.016)	(0.016)
Log(1 + CapExpPS)	−0.032	−0.032	−0.060	−0.061	−0.018	−0.018
	(0.023)	(0.023)	(0.054)	(0.054)	(0.016)	(0.016)
ROA	0.001	0.001	0.002	0.002	0.001	0.001
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
AssetGr	−0.000	−0.000	0.001***	0.001***	−0.000*	−0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
HLTH		−0.004***		0.004*		0.027***
		(0.001)		(0.002)		(0.002)
MANUF		−0.127		−0.017		29.178***
		(0.095)		(0.277)		(1.956)
ENINT		−4.187***		5.950***		−63.231***
		(0.403)		(1.510)		(2.438)
ELRENEW		0.174***		0.084		5.178***
		(0.027)		(0.100)		(0.402)
EPS		15.481***		−8.837		22.169***
		(2.694)		(5.959)		(2.072)
GCRI		0.113**		−0.037		−2.570***
		(0.048)		(0.175)		(0.159)
Constant	0.073***	−0.206**	0.085**	−0.016	0.132***	−2.566***
	(0.018)	(0.095)	(0.040)	(0.223)	(0.019)	(0.294)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.026	0.069	0.069	0.017	0.017
Observations	2691	2675	758	750	1933	1925

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table presents the OLS estimates of Eq. (2). The dependent variable is the stock cumulative return in 2016. *Emission* is a dummy variable that is equal to one if the firm i in 2016 belongs to an industry classified as carbon-intensive according to IPCC and zero otherwise. *MTB* is the market-to-book ratio, *MktCap* is market capitalization, *CapExp* denotes capital expenditure per share, *ROA* is return on assets, *AssetGr* is asset growth. The remaining variables are defined in the note to Table 2.

worried regions, the coefficient of *Emission* is negative but not statistically significant. In line with previous literature, we do not find any significant relationship between emission intensity and stock returns (Bolton and Kacperczyk, 2021; Aswani et al., 2023). Since emission data are available only for a small number of firms in what follows we use the IPCC definition to identify emission stocks.

Table 6: Returns of emission and clean stocks - Robustness

	All sample		Little worried		Worried	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Total emissions						
Emission	0.032**	0.032**	−0.009	−0.009	0.032**	0.032**
	(0.015)	(0.015)	(0.053)	(0.053)	(0.016)	(0.016)
MTB	−0.004*	−0.004*	−0.028***	−0.028***	−0.007**	−0.007**
	(0.002)	(0.002)	(0.007)	(0.007)	(0.003)	(0.003)
log(1 + MktCap)	−0.011	−0.011	0.020	0.020	−0.002	−0.002
	(0.012)	(0.012)	(0.030)	(0.030)	(0.015)	(0.015)
log(1 + CapExpPS)	−0.124***	−0.124***	−0.187***	−0.187***	−0.107*	−0.107*
	(0.046)	(0.046)	(0.053)	(0.053)	(0.057)	(0.057)
ROA	0.006***	0.006***	0.017	0.017	0.008***	0.008***
	(0.002)	(0.002)	(0.016)	(0.016)	(0.002)	(0.002)
AssetGr	−0.000***	−0.000***	−0.005	−0.005	−0.000***	−0.000***
	(0.000)	(0.000)	(0.005)	(0.005)	(0.000)	(0.000)
Constant	−0.157***	0.682**	−0.131	1.698***	−0.270***	−7.171
	(0.026)	(0.278)	(0.102)	(0.425)	(0.067)	(5.801)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	No	Yes	No	Yes	No	Yes
R^2	0.410	0.410	0.672	0.672	0.401	0.401
Observations	519	519	117	117	402	402
Panel B: Emission intensity						
Emission	0.003	0.003	−0.046	−0.046	0.013	0.013
	(0.008)	(0.008)	(0.031)	(0.031)	(0.015)	(0.015)
MTB	−0.005*	−0.005*	−0.035***	−0.035***	−0.009***	−0.009***
	(0.003)	(0.003)	(0.013)	(0.013)	(0.003)	(0.003)
log(1 + MktCap)	0.008	0.008	0.021	0.021	0.022**	0.022**
	(0.012)	(0.012)	(0.034)	(0.034)	(0.010)	(0.010)
log(1 + CapExpPS)	−0.118**	−0.118**	−0.198***	−0.198***	−0.105*	−0.105*
	(0.047)	(0.047)	(0.056)	(0.056)	(0.059)	(0.059)
ROA	0.006***	0.006***	0.015	0.015	0.008***	0.008***
	(0.002)	(0.002)	(0.016)	(0.016)	(0.001)	(0.001)
AssetGr	−0.000***	−0.000***	−0.005	−0.005	−0.000***	−0.000***
	(0.000)	(0.000)	(0.004)	(0.004)	(0.000)	(0.000)
Constant	−0.167***	0.768***	−0.116	1.633***	−0.118***	−4.102
	(0.025)	(0.285)	(0.175)	(0.403)	(0.043)	(6.395)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-level controls	No	Yes	No	Yes	No	Yes
R^2	0.432	0.432	0.692	0.692	0.451	0.451
Observations	517	517	117	117	400	400

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table presents the OLS estimates of Eq. (2). The dependent variable is the stock cumulative return in 2016. In Panel A, *Emission* is a firm's scope 1 and 2 total CO_2 equivalent emissions in 2016. In Panel B, *Emission* is a firm's emission intensity (scope 1 and 2 emissions divided by total revenue) in 2016. *MTB* is the market-to-book ratio, *MktCap* is market capitalization, *CapExp* denotes capital expenditure per share, *ROA* is return on assets, *AssetGr* is asset growth. Country-level control variables are defined in the note to Table 2.

4.2 Propensity score matching analysis

In order to rule out that the difference in returns of emission and clean stocks is due to other factors, we employ matching techniques: firm propensity to be carbon-intensive is used to match emission stocks with otherwise similar clean stocks to evaluate the presence of a carbon premium. The propensity score matching (PSM) consists of two stages: in the first one, a logit regression model for emission stocks is estimated in order to build a counterfactual sample. Conditional on satisfying the balancing property of the propensity score, the fitted values obtained from the logit regression model estimation are used to pair up emission with clean stocks. Matching is performed according to the optimal full matching method (Hansen, 2004; Hansen and Klopfer, 2006), which is a form of sub-classification wherein all units, both treatment (emission stocks) and control (clean stocks), are assigned to a subclass and receive at least one match. The matching is optimal in the sense that the sum of the absolute distances between the treated (emission stocks) and control (clean stocks) units in each subclass is as small as possible. Optimal full matching does not require specifying the matching order; moreover, it does not discard any units, and it is less likely that extreme within-subclass distances will be large. We perform optimal full matching using the *MatchIt* package (Stuart et al., 2011) in R. The matched pairs are subsequently used to estimate the average treatment effect of being an emission firm on returns. The PSM requires that all variables relevant to the probability of being an emission firm be observed and included in the logit regression model. Moreover, in order to find adequate matches, it is necessary to ensure sufficient overlap in the characteristics of emission and clean stocks. While the last assumption can be easily tested, the first one is difficult to satisfy. The matching procedure between emission and clean stocks is based on the entire set of regressors in Eq. (2).[14]

In Table 7, we report the average treatment effect on the treated (ATET) obtained by PSM.[15] The ATET confirms previous results concerning the presence of a carbon premium when we consider either the whole sample or only worried regions. Differently, in little worried regions, emission and clean stocks with similar characteristics do not show any significant difference in average returns.[16]

[14]Figure 7 in Appendix D shows the histograms of the propensity scores before and after matching for both the treated (emission stocks) and control (clean stocks) groups in the case of the average treatment effect on the treated (ATET) estimations for the whole sample. The histograms indicate covariate balance.

[15]Results regarding the first-step logit regression models are reported in Table 12 in Appendix D.

[16]We have estimated the ATET using alternative matching methods including the nearest neighbor matching and the optimal pair matching. Results do not change and they are available upon request.

Table 7: Propensity score matching (ATET)- Returns and emission vs clean stocks

	Estimate	Std. Error	Statistic	p-value	Obs
Whole sample	0.0770***	0.0275	2.7976	0.0052	2675
Little worried	0.0190	0.0512	0.3714	0.7104	750
Worried	0.1284***	0.0335	3.8289	0.0001	1925

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Treatment variables are emission dummies. The estimated coefficient represents the average difference in return between emission and clean stocks with similar characteristics. The selection of the control group is based on the entire set of control variables: MTB, market capitalization, capital expenditure per share, ROA, asset growth, exchange cities dummies, country's health expenditures per capita, percentage of a country's GDP that is produced in a given year in the manufacturing sector, country's energy intensity, country's share of electricity generated by renewable power plants, country's environmental policy stringency index, and country's climate risk index. We adopt the optimal full-matching method.

4.2.1 Robustness test

In Table 2, we have shown that worries about climate change tend to be higher in less economically developed areas (lower $MANUF$) and areas more dependent on non-renewable sources for electricity production (lower $ELRENEW$). Since worries about climate change might be proxying for some economic measures, we compute the average treatment effect of being an emission firm on returns for countries with high/low $MANUF$ and $ELRENEW$. We use the median to identify the two subsamples, but the results are robust to the use of other quantiles. The selection of the control group is based on the entire set of control variables including the worry index. Table 8 reports the results, we can observe that the carbon risk premium is significant in all subsamples which implies that the worry index is not proxying for economic development nor dependence on renewable energy sources.

4.2.2 Quantile treatment effect

We complement the matching analysis on the average effects employing quantile treatment effect (QTE) using matching techniques (Firpo, 2007) to examine the heterogeneity in the difference in returns of emission and clean stocks. This method allows for a more accurate assessment of the relation under study since it compares similar firms in terms of their probability of being carbon-intensive and it estimates these effects taking into account the unconditional distribution of the outcome variable (i.e., cumulative return). This method is based on the conditional independence assumption which describes the

Table 8: Propensity score matching (ATET)- Robustness

	Estimate	Std. Error	Statistic	p-value	Obs
Panel A: Economic development					
Low MANUF	0.1124*	0.0657	1.7093	0.0878	828
High MANUF	0.0589**	0.0270	2.1843	0.0291	1847
Panel B: Renewable energy					
Low ELRENEW	0.1003**	0.0402	2.4934	0.0128	864
High ELRENEW	0.0663*	0.0364	1.8208	0.0688	1811

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Treatment variables are emission dummies. The estimated coefficient represents the average difference in return between emission and clean stocks with similar characteristics. In Panel A, we report the results separately for countries with high/low percentage of a country's GDP that is produced in a given year in the manufacturing sector. In Panel B, we report the results separately for countries with high/low share of electricity generated by renewable power plants. The selection of the control group is based on the entire set of control variables including the worry index. We adopt the optimal full-matching method.

difference in the quantiles of the outcome variable (returns) for emission and clean stocks without reference to the control variables. Indeed, the covariates are used only to estimate the propensity score of the probability of being an emission firm, thus allowing the comparison of similar stocks. Different from the standard quantile regression (QR), the definition of unconditional QTE does not change when we change the set of covariates. Consider for example returns and size, the unconditional 90^{th} percentile of returns refers to stocks with high returns, whereas the 90^{th} percentile of returns conditional on size refers to stocks with high returns within each size class, which may not be high returns overall. Therefore, the interpretation of the 90^{th} quantile is different if one considers conditional and unconditional quantiles. A shortcoming of the unconditional QTE estimator by Firpo (2007) is that it relies on the assumption of exogeneity of the treatment variable. Hence, although QTE should provide more accurate estimates compared with standard QR, we cannot claim that the results correspond to causal effects.

Figure 2 confirms that the difference in return of emission and clean stocks tends to be not significant when investors are only a little worried about climate change. However, in the whole sample and worried regions, we find that the return premium of emission stocks increases when considering higher quantiles of the return distribution and it is significantly different from zero only for medium-high quantiles.

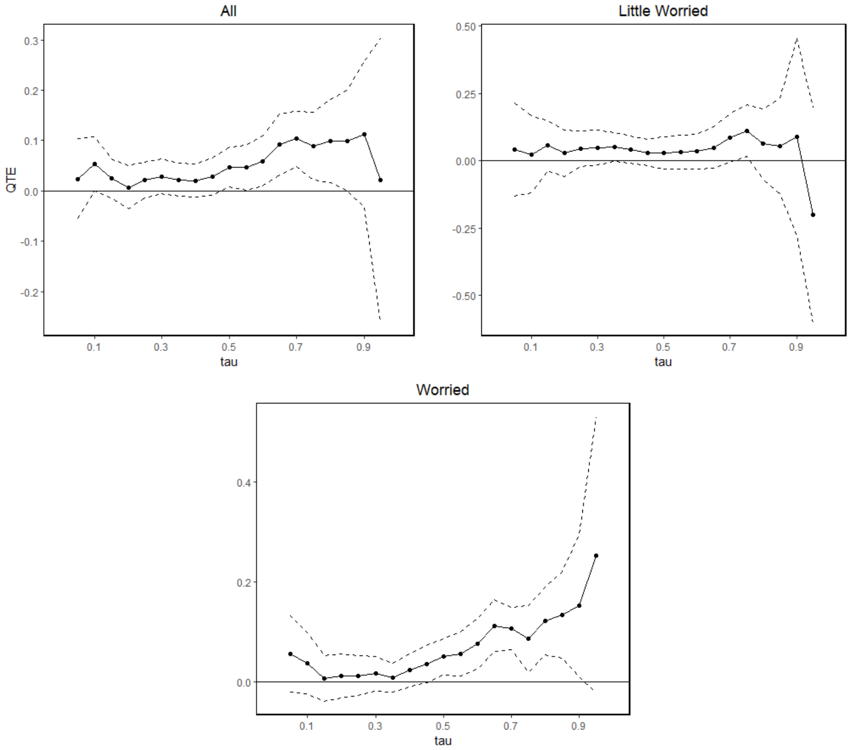

Figure 2: Quantile Treatment Effect.

Notes: Treatment variables are emission dummies. The estimated coefficient represents the quantile difference in return between emission and clean stocks with similar characteristics. Dashed lines are 95% confidence intervals. The selection of the control group is based on the entire set of control variables: MTB, market capitalization, capital expenditure per share, ROA, asset growth, exchange cities dummies, country's health expenditures per capita, percentage of a country's GDP that is produced in a given year in the manufacturing sector, country's energy intensity, country's share of electricity generated by renewable power plants, country's environmental policy stringency index, and country's climate risk index. Standard errors are computed with Bootstrap (1000 iterations).

5 Discussion of results

The level of emissions can affect stock returns through several channels. First, stocks of carbon-intensive firms have a higher exposure to transition risk as they may become the target of regulatory interventions aiming to reduce emissions. Hence, investors may seek compensation for holding stocks highly exposed to carbon risk. In this case, we should observe a positive relationship between the level of emissions and stock returns (Bolton and Kacperczyk, 2021, 2023; Hsu et al., 2023). Consistent with this hypothesis, we find that emission stocks have higher returns than clean stocks when investors are worried about climate change.

Second, financial markets may price carbon risk inefficiently by ignoring information about climate change and its related risks. Carbon risk might be underpriced to the point where responsible investors might achieve better performance by investing in clean stocks, that is the carbon risk premium can become negative (In et al., 2019). In this study, we do not find evidence of a carbon risk premium when investors are only slightly worried about climate change. Little worried investors tend to overlook information on the firm exposure to long-run transition risk which may lead to mispricing. Moreover, we observe that the carbon risk premium is not significant for low-return stocks. Investors underprice the carbon risk of low-return stocks as they are more likely to attract low analyst coverage and attention.

Third, emission stocks can be seen as 'sin stocks' (Hong and Kacperczyk, 2009). Hence, responsible investors may divest from these stocks to such an extent that they present higher stock returns. Although there is evidence of institutional investors divesting from fossil fuel companies, the literature suggests that the carbon risk premium is not caused solely by divestment (Bolton and Kacperczyk, 2021, 2023).

6 Conclusions

Climate change is a very debated and controversial topic. This paper employs small area estimation methods to develop a regional indicator of worry about climate change using data from the European Social Survey Round 8 (ESS, 2016). We use the level of worry about climate change of regions with an exchange city as a proxy of investors' worries about climate change. Indeed, investors tend to be located in the surroundings of exchange cities (see Chan et al., 2003; Choi et al., 2020). Then, we study the link between the carbon risk premium and investors' worry about climate change.

We show that worries about climate change are higher in less economically developed areas and areas more dependent on non-renewable sources for electricity production. More importantly, we find that on average investors underprice the carbon risk when they are only a little worried about climate change. We argue that these investors may neglect information on firms' exposure to carbon risk which can lead to mispricing. Furthermore, the carbon premium is significant for medium-high quantiles of the return distribution when investors' worries are high.

This study has important practical implications. Investors and practitioners can use these results to inform the construction of their investment portfolios. Moreover, these results are relevant to policymakers because we have shown that financial markets do not fully price carbon transition risk hence market forces alone cannot be an alternative to a global carbon tax to achieve emissions reduction.

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A Industry classification

Table 9: Summary of Industry Information

INDG Code	Industry Name	IPCC Code	Industry Name
Energy			
97	Integrated Oil & Gas	1A1bc	Other Energy Industries
50	Oil: Crude Producers	1B2	Flaring and fugitive emissions from oil and Natural Gas
263	Offshore Drill. & Other Serv.	1B2	Flaring and fugitive emissions from oil and Natural Gas
240	Oil Refining & Marketing	1B2	Flaring and fugitive emissions from oil and Natural Gas
51	Oil Equipment & Services	1A1bc	Other Energy Industries
49	Coal	1A2f4	Mining and quarrying
169	Conventional Electricity	1A1a	Power and Heat Generation
31	Gas Distribution	1A3e, 1B2	Non-road transport (fossil), Flaring and fugitive emissions from oil and Natural Gas
Transport			
129	Airlines	1A3a, 1C1	Domestic air transport, International aviation
131	Trucking	1A3b	Road transport (includes evaporation) (fossil)
81	Railroads	1A3c	Rail transport
99	Marine Transportation	1A3d, 1C2	Inland shipping (fossil), International navigation
40	Delivery Services	1A3er	Non-specified transport
64	Transportation Services	1A2f2, 1A3b	Transport equipment, Road transport (fossil) (includes evaporation)
52	Pipelines	1A3e1	Pipeline transport
Buildings			
36	Home Construction	1A4b	Residential (fossil)
30	Building Materials: Other	1A4a, 2A1	Commercial and public services (fossil), Cement production
39	Construction	1A2f6	Construction
229	Machinery: Construction and Handling	1A2f3	Machinery
Industry			
130	Semiconductors	2F7a	Semiconductor Manufacture
65	Automobiles	1A2f2	Transport equipment
63	Auto Parts	1A2f2	Transport equipment
71	Food Products	1A2e	Food and tobacco
79	Tobacco	1A2e	Food and tobacco
69	Clothing and Accessories	1A2f7	Textile and leather
254	Textile Products	1A2f7	Textile and leather
258	Electrical Components	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
213	Electronic Equip.: Control	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
214	Electronic Equip.: Gauges	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture

(continued)

continued

INDG Code	Industry Name	IPCC Code	Industry Name
57	Electronic Equip.: Other	2F7a, 2F8a	Semiconductor Manufacture, Electrical Equipment Manufacture
230	Machinery: Engines	1A2f3	Machinery
43	Machinery: Industrial	1A2f3	Machinery
232	Machinery: Tools	1A2f3	Machinery
231	Machinery: Specialty	1A2f3	Machinery
117	Commercial Vehicles & parts	1A2f2	Transport equipment
82	Paper	1A2d	Pulp and paper
122	General Mining	1A2f4	Mining and quarrying
56	Iron & Steel	1A2a	Iron and steel
93	Aluminum	1A2b, 2C3	Non-ferrous metals, Aluminum production (primary)
54	Nonferrous Metals	1A2b	Non-ferrous metals
119	Gold Mining	1A2f4	Mining and quarrying
78	Plat.& Precious Metal	2Cr	Non-ferrous metals production
92	Chemicals: Diversified	1A2c	Chemicals
207	Chemicals and Synthetic Fibers	1A2c	Chemicals
217	Fertilizers	1A2c	Chemicals
33	Specialty Chemicals	1A2c	Chemicals
241	Paints & Coatings	3A	Solvent and other product use: paint
206	Cement	2A1	Cement production
91	Multi-utilities	1A1a, 1A2f	Power and Heat Generation, Other industries (stationary) (fossil)
47	Waste & Disposal Svs.	6A	Solid waste disposal on land
AFOLU			
35	Farming, Fishing, Ranching and Plantations	1A4c3, 4A, 4B, 4C, 4Dr	Fishing (fossil), Enteric Fermentation, Manure management, Rice cultivation, Agricultural soils (direct)
38	Forestry	1A4c1	Agriculture and forestry
228	Machinery: Agricultural	1A2f3, 1A4c2	Machinery, Off-road machinery: agric./for.

Notes: The table presents a list of Datastream level 6 industrial classification codes available from Refinitiv Eikon Datastream and the matching IPCC category codes which are classified as carbon intensive.

B Small area estimation evaluations

In this Appendix, we discuss the results of the Confirmatory Factor Analysis (CFA) model used to estimate worry about climate change at the respondent level and small area estimation diagnostics (Brown et al., 2001).

The CFA model shows a good model fit. In particular, the Standardized Root Mean Square Residual (SRMR) is equal to 0.060 and the Comparative Fit Index (CFI) is equal to 0.901. The literature identifies a good model fit as $SRMR < 0.08$ and $CFI \geq 0.90$ (Hu and Bentler, 1999). Given the positive values of the factor loadings[17] between the observed variables and the latent variable estimated from the CFA model, when the indicator takes larger values, this denotes more worries about climate change. In this work, we are interested in the mean of this indicator for the European regions.

Table 10 shows the results of the Fay-Herriot regional-level regression model used to estimate the fixed effects and variance of the error term to produce the model synthetic regional estimates and shrinkage factor. The dependent variable is the direct regional estimate of worry about climate change which is computed from ESS survey data, and explanatory variables are regional-level variables retrieved from the Eurostat Regional

Table 10: Fay-Herriot Regional-level model results

	Estimate	Std.Dev	p-value
Age 15-29	-2.066^{***}	0.514	0.000
Age 30-49	-1.175^{***}	0.445	0.005
Age 50-64	-0.635	0.483	0.188
Age 65-84	-1.274^{***}	0.365	0.000
Age over 85	-0.860	1.433	0.549
Male	-1.012^{**}	0.438	0.021
GDP per capita	-0.378^{***}	0.105	0.000
Married	0.194^{*}	0.102	0.058
Primary and Lower Secondary Education	-0.001	0.003	0.805
Tertiary Education	0.004	0.003	0.103
Constant	1.823^{***}	0.447	0.000

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. This table presents the results of the Fay-Herriot regional-level model. The dependent variable is the direct regional estimate of worry about climate change which is computed from ESS survey data, and explanatory variables are regional-level variables retrieved from the Eurostat Regional Statistics database.

[17]The factor loadings measure the correlation between the observed variables and the latent variable (worry about climate change).

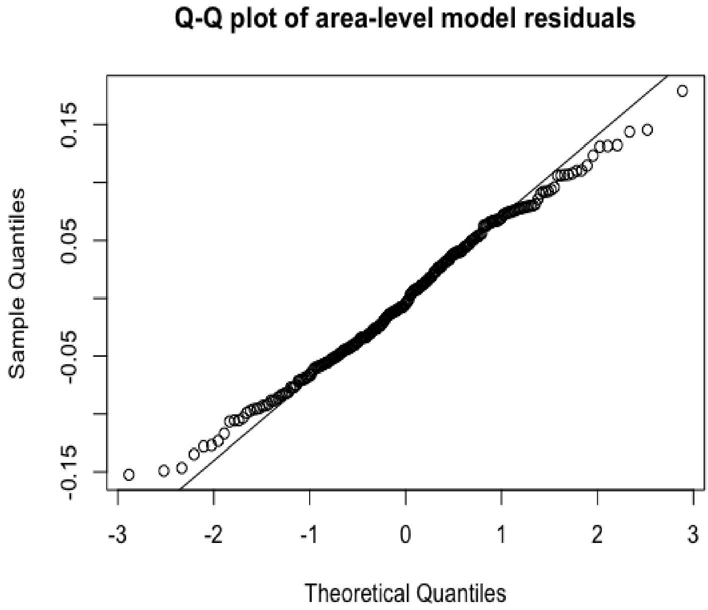

Figure 3: Normal Q-Q plot of regional-level residuals.

Statistics database. As explained in Section 3, the synthetic estimates are then combined with the direct regional estimates using the shrinkage factor to produce the final small area estimates (Fay and Herriot, 1979). The shrinkage factor attaches more weight to the direct estimates when these are more reliable (the regional sample size is large), and conversely less weight to the synthetic estimates, and vice-versa.

As shown in Figure 3, the Q-Q plot of the regional-level model residuals (model given in Table 10) shows that the residuals are approximately Normally distributed. In addition, given that our aim is to improve the survey-based direct regional estimates, without introducing bias in the final small area estimates, we estimate Spearman's ranking correlation coefficient between the direct and model-based estimates and this returns good results (value equal to 0.94). The scatter plot of EBLUP and direct regional estimates is available in Figure 4. Furthermore, we show in Figure 5 that the use of EBLUP approach produces more efficient estimates than the direct estimator, in fact, the Relative Root Mean Squared Error (RRMSE) of the EBLUPs is always smaller than the Coefficient of Variation (CV) of the direct estimates across the regions. In particular, we note that the RRMSE is always considerably below 20%, which means that the estimates are of a good quality according to Official Statistics guidelines (see e.g., Spagnolo et al., 2018).

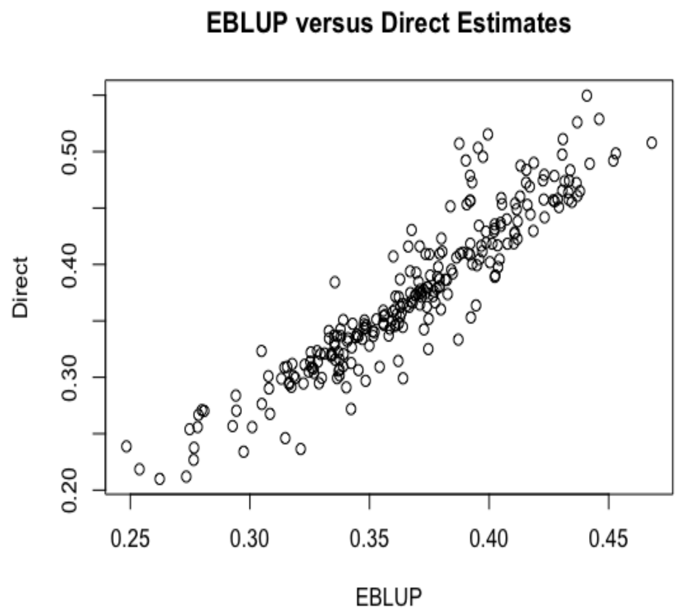

Figure 4: Scatter plot of EBLUP and direct estimates.

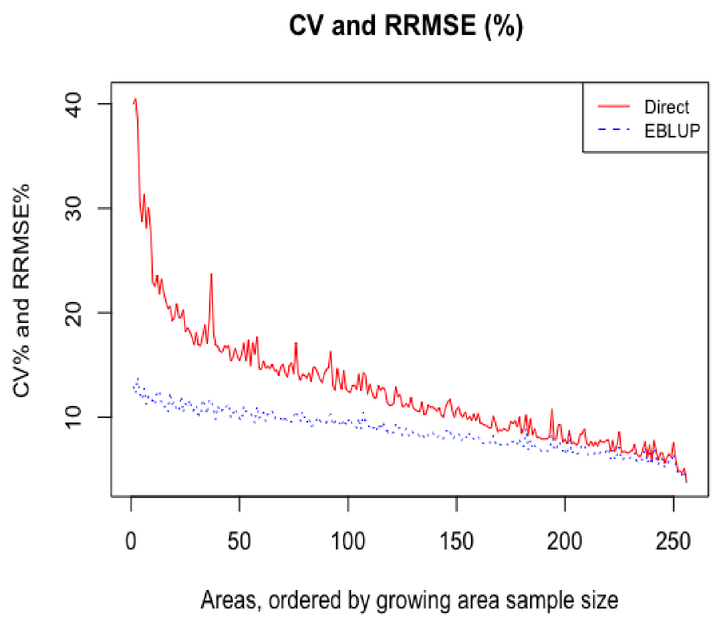

Figure 5: Percentage Coefficient of Variance (CV) for direct estimates and Relative Root Mean Squared Error (RRMSE) for EBLUPs.

C More on worries about climate change

As we have already discussed, the ESS is not designed to produce reliable estimates and analyses at the sub-national level (ESS, 2016). Hence, we employ small area estimation methods (Rao and Molina, 2015) to estimate a regional indicator of worry about climate change. We do so because we propose to use the level of worry of regions with an exchange city as a proxy of investors' worry about climate change. In Table 11, we test the difference of the worry indicator in regions with and without an exchange city. The two-sample Fligner-Policello (FP) robust rank order test (Fligner and Policello, 1981) fails to accept the null hypothesis that the level of worries about climate change is the same in regions with and without an exchange city. In particular, regions with an exchange city show a significantly lower level of worry about climate change than the other regions. We can conclude that it is important to use regional estimates rather than country estimates to proxy for the level of worry about climate change of investors.

Another concern of this analysis is that the level of worry about climate change might have evolved since 2016, the year in which the questions on "Public attitudes to climate change" were included in the ESS. To address this concern, we analyse the answers to the question "How worried are you about climate change?" which was repeated also in round 10 of the ESS. In Figure 6, we present a paired bar plot of the weighted country proportions of the respondents who are at least somewhat worried about climate change in 2016 and 2020. We can observe that in almost all countries the proportion of worried respondents has increased, although the increase is generally small.

Table 11: Two-sample Fligner Policello Robust Rank Order Test

	Observations	Mean	St. Dev.	Statistic	2-tailed p-value
Exchange city	23	-0.403	0.995	1.969	0.049
Non exchange city	230	0.040	0.956		

Notes: The table presents the results of the two-sample Fligner Policello robust rank order test on the normalized regional indicator of climate change worries for regions with and without an exchange city. We excluded from the sample Iceland, Estonia, and Portugal which have less than 5 regions.

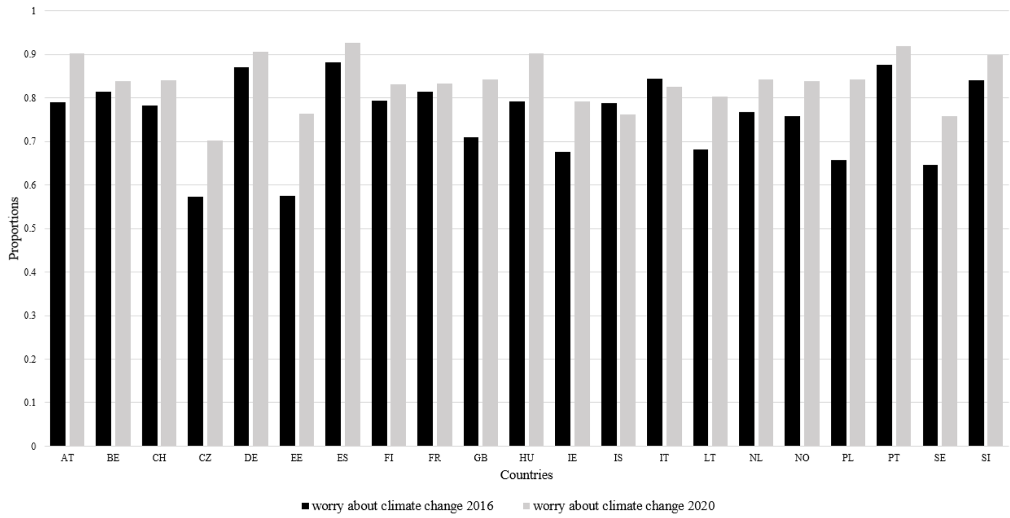

Figure 6: Comparison of worry about climate change in 2016 and 2020.

Notes: The figure displays a paired bar plot of the weighted country proportions of the respondents who answered at least somewhat worried to the question "How worried are you about climate change?" which was included in the European Social Survey both in round 8 and 10.

D Propensity score matching

Treatment effect estimators re-weight the observational data to achieve experimental-like balanced data results. If the re-weighting is successful, then the weighted distribution of each covariate should be the same across treatment groups. In such cases, we say that the treatment model 'balanced' the covariates.

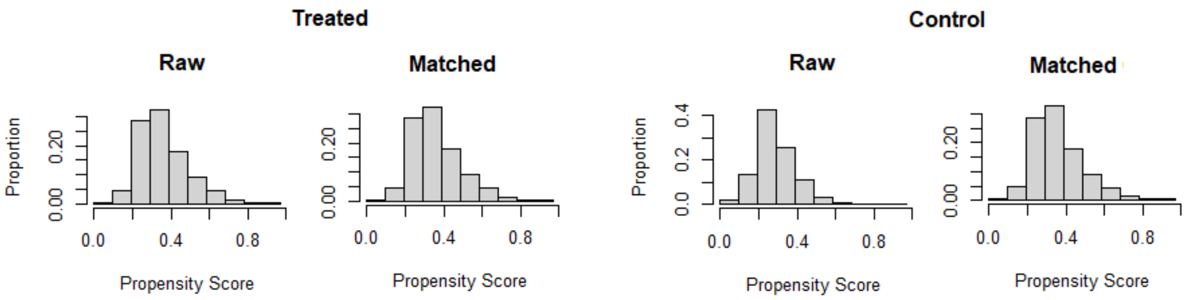

Figure 7: Balance Plot

Notes: The figure shows the histograms of the propensity scores before and after matching for both the treated (emission stocks) and control (clean stocks) groups in the case of the average treatment effect on the treated (ATET) estimations for the whole sample.

Table 12: First-step of the PSM estimates: Logit model

Regions	All sample	Little worried	Worried
Constant	−1.185	−4.052	19.734**
	(2.277)	(3.010)	(9.123)
MTB	−0.008	0.015	−0.027**
	(0.009)	(0.012)	(0.013)
log(1 + MktCap)	−0.053	−0.034	−0.061
	(0.057)	(0.102)	(0.069)
log(1 + CapExpPS)	0.699***	0.613***	0.742***
	(0.081)	(0.150)	(0.096)
ROA	−0.004*	−0.003	−0.005*
	(0.002)	(0.004)	(0.003)
AssetGr	−0.006***	−0.009***	−0.006***
	(0.001)	(0.003)	(0.001)
HLTH	−0.018	0.075**	−0.156**
	(0.024)	(0.037)	(0.065)
MANUF	1.738	8.082	−149.153**
	(6.575)	(8.006)	(73.609)
ENINT	12.509	216.108**	212.034
	(48.750)	(86.060)	(140.730)
ELRENEW	0.555	−3.566*	−31.801**
	(0.903)	(1.986)	(15.061)
EPS	−9.912	−32.747	−150.379*
	(66.183)	(37.017)	(84.337)
GCRI	0.420	−7.889***	12.764**
	(0.904)	(2.859)	(6.158)
Exchange city FE	Yes	Yes	Yes
Observations	2675	750	1925

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. The table reports the results of the logit regression used in the first-step of the propensity score matching.

Figure 7 shows the histograms of the propensity scores before and after matching for both the treated (emission stocks) and control (clean stocks) groups in the case of the average treatment effect on the treated (ATET) estimations for the whole sample. It can be seen that the histograms of the matched treated and control groups are very similar which indicates covariate balance.

Results regarding the first-step logit regression models are reported in Table 12. We can observe that capital expenditure and asset growth appear to be the most important firm-level variables in determining the likelihood of a stock being classified as carbon-intensive. On the contrary, the stock's size is not significant. Moreover, in worried regions lower levels of MTB and ROA are most likely to be observed in emission stocks rather than clean stocks. We also find that in little worried regions, the likelihood to observe an emission stock rather than a clean stock is higher in those countries with a higher level of economic development, energy intensity, exposure to climate physical risk, and lower use of renewable energy sources. Differently, we find that in worried regions the likelihood to observe an emission stock rather than a clean stock is higher in those countries with a lower level of economic development, use of renewable energy sources, environmental policies stringency, and exposure to climate physical risk.