Carbon Risk Premium and Worries about Climate Change [*,†]

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Abstract

This paper sheds light on the impact of public attitudes towards climate change on the pricing of emission (carbon-intensive) and clean (low-emission) stocks. We develop a regional indicator of worries about climate change using data from the European Social Survey Round 8. We classify European regions as little worried, worried and very worried. We confirm previous evidence that emission stocks tend to have higher returns than clean stocks. However, when we focus on stocks quoted in exchange markets located in regions with low level of worries about climate change, we do not find evidence of a carbon risk premium. Conversely, the carbon premium in worried regions is significant for medium-high quantiles of the return distribution.

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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 wants to understand 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 allowing a better allocation of resources.

Recently, Bolton and Kacperczyk (2021a) and Hsu et al. (2022) have shown that stocks of carbon-intensive firms tend to outperform stocks of firms with lower level of emissions. This difference in returns cannot be explained by common risk factors and it has been attributed to carbon risk. In this paper, we study whether this evidence holds in European regions where the level of worries about climate change is low. In particular, by worries about climate change, we mean worries about the risks posed by the transition towards carbon-neutrality. Our hypothesis is that lower level of worries may induce investors to neglect information on firms' exposure to carbon risk and hence not pricing 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). Moreover, emotional factors such as climate sentiment impact the stock pricing of emission and clean firms (Bessec and Fouquau, 2020; Santi, 2020; Briere and Ramelli, 2021).

We develop a regional indicator of worries about climate change from the answers to the questions on "Public attitudes to climate change" of the European Social Survey (ESS) Round 8 (ESS, 2016). Since the ESS is not designed to produce reliable estimates and analyses at 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 contributions in the field. Moreover, these approaches are part of the methods used in Official Statistics (see e.g., Rao and Molina, 2015). We employ Thomson Reuters Datastream to retrieve data on adjusted closing prices, market capitalization, and other company information. We consider stocks traded in several European financial markets, in each market we focus on primary quotes to avoid cross-listings. 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; Santi, 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.[1] 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.

Importantly, we show that the difference in returns of emission and clean stocks depends on investors worries about climate change. First, we propose the use of the worry index for the region where the exchange city is located as a proxy of investors worries about climate change. This is consistent with the evidence that investors tend to be located in the exchange cities and their surroundings, and that prices are affected by domestic investors (see Choi et al., 2020; Chan et al., 2003). Then, we investigate the difference in returns of emission and clean stocks in all the European regions, little worried and worried regions using a plethora of statistical methods. Consistent with Hsu et al. (2022) and Bolton and Kacperczyk (2021a), we find that emission stocks have significantly higher returns than clean stocks when we either consider the whole sample or worried regions. However, when we focus on little worried regions, we do not find any significant difference in the average return of emission and clean stocks. To gain further insight on this issue, we use quantile regression analysis to take into account for the heterogeneity in stock returns. We show that in little worried regions the difference in returns of emission and clean stocks is significant only for high-return stocks. This finding is consistent with investors paying more attention to high-return stocks and neglecting information on the environmental impact of firms reporting medium-low stock returns hence not pricing their carbon risk.

We present additional evidence using matching techniques (Firpo, 2007), which allow us to estimate the difference in returns of emission and clean stocks along the distribution of returns by comparing emission and clean firms with similar characteristics. When we use matching techniques, the carbon premium in worried regions is significant only for medium-high quantiles. In contrast, the difference in return of emission and clean stocks is significant only at the 75^{th} percentile (5% confidence level) in little worried regions. Results are robust to differences in the stringency of local environmental policies.

In summary, this study sheds light on the importance of investors' worries on climate

[1]Note that due to limited data availability, we cannot use firm's carbon emissions data from the Carbon Disclosure Project (CDP) or Environmental, Social, Governance (ESG) data providers (i.e., MSCI, Sustaynalitics, Refinitiv ESG) to distinguish between emission and clean stocks.

change in the pricing of high/low emission stocks. In particular, we find that investors do not price the carbon risk of stocks quoted in exchange cities located in regions only little worried about climate change. We also document that investors tend to neglect information on the environmental impact of low-return stocks.

This paper contributes to the literature in several ways. First, we address the heterogeneous spatial distribution of public attitudes towards climate change in Europe. Several recent studies use newspaper articles to measure concerns about climate change (Ardia et al., 2020; Engle et al., 2020). 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 on a certain topic. Moreover, even though our survey data do not allow us to study the evolution over time of public attitudes on climate change, we can perform a spatial comparison at regional level which cannot be done with data from national newspapers. To the best of our knowledge, our study is the first work to provide evidence on the differences among European regions concerning the link between the carbon risk premium and worries about climate change. Second, we add to the cross-country evidence on the pricing of emission and clean stocks. Choi et al. (2020) considers a total of 74 exchange cities and they show that attention on global warming increases when temperatures are abnormally high. Further, they document that retail investors sell stocks of emission firms in such weather conditions. Also related to our paper is the study by Bolton and Kacperczyk (2021b) who analyse the carbon risk premium in a cross-section of 14,400 firms in 77 countries. They show that the carbon risk premium is related to countries characteristics such as level of economic development, size of the energy sectors, inclusiveness of the political systems, and stringency of 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 premium, especially in Asia, following the signature of the Paris agreement. Our contribution differs from the above two studies as we focus on the link between worries about climate change and the carbon risk premium, moreover we explore this link along the quantiles of the return distribution. The paper is also related to the country-level literature on carbon risk. Bolton and Kacperczyk (2021a) 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. (2022) 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.

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 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 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 Worries about Climate Change

Public attitudes towards climate change are a latent multidimensional phenomenon. This means that their measurement requires to consider multiple dimensions such as worries about natural disasters, use of fossil fuels, price of energy, and other related issues (Whitmarsh, 2011). The variables used to construct the regional indicator of worries about climate change are from the European Social Survey (ESS) 2016 round 8 (ESS, 2016). ESS is a nationally representative European cross-national sample survey that has been running since 2001 bi-annually.[2] 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 choose ESS round 8 because it is the only round where data on the topic "Public attitudes to climate change" is collected. In order to analyse worries about climate change cross-nationally across Europe we focus on nine ESS items identified by Poortinga et al. (2018) and also available in the ESS round 8 data.

The questions used are phrased in the questionnaire as follows:

1. How worried are you about climate change?

[2]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.

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). Note that given the above questions, in what follows by worries about climate change we mean worries about the risks posed by the transition towards carbon-neutrality.

The auxiliary variables used to produce the small area estimates in Section 3.2 are taken from Eurostat Regional Statistics database.[3] These variables are area-level variables (measured at regional level) and are: 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, proportion of married citizens, proportion of citizens with primary and lower secondary education qualification, and proportion of citizens 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, as it is shown in Appendix B, the use of these variables produce excellent small area model's performance.

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

2.2 Stock and Company Information

We employ Thomson Reuters Datastream to retrieve data on adjusted closing prices, market capitalization, and other company information. We consider stocks traded in several European financial markets, in each market we focus on primary quotes to avoid cross-listings.[4] 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. For each stock, we compute the cumulative returns of the year 2016, and we remove stocks with missing observations in that year.

Following Choi et al. (2020), we classify stocks as either emission or clean according to their industry. The Intergovernmental Panel on Climate Change (IPCC) identifies five major industry sectors as major emission sources: Energy; Transport; Buildings; Industry (such as chemicals and metals); and Agriculture, Forestry, and Other Land Use (AFOLU).[5] We manually match the Datastream level 6 industrial classification codes with the IPCC category codes.[6] All firms in the matched industries are classified as emission (carbon-intensive) firms, the rest is classified as clean (low-emission) firms. Our dataset includes a total of 5,688 stocks, 4,603 clean stocks (average cumulative return 6.75%) and 1,082 emission stocks (average cumulative return 14.86%).

Alternative ways to identify emission and clean stocks consist in using firm-level emission data from either the Carbon Disclosure Project (CDP) or Environmental, Social, and Governance (ESG) data providers such as MSCI, Sustainalytics, and Refinitiv ESG (formerly ASSET4). However, these data cover only a small subset of European firms in 2016 which makes it impossible to conduct the analysis of this study. Moreover, industries are a popular investment style, hence we expect investors without access to firm-level carbon emission data to use industries to differentiate between emission and clean stocks.

We also consider a set of firms' characteristics for the fiscal year 2015. Market-to-

[4]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.

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

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

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 closing price of the company's stock at their fiscal year end and 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 1 year annual percentage growth of total assets. We winsorize 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. Moreover, for most of the 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, Asset growth of emission stocks is lower than 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						

(continued)

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Countries	Returns	MTB	Market Cap (€ Mil.)	Cap. Exp. per share (€)	ROA (%)	Asset Growth (%)
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
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

(continued)

continued

Countries	Returns	MTB	Market Cap (€ Mil.)	Cap. Exp. per share (€)	ROA (%)	Asset Growth (%)
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.

3 Regional indicator of worries on climate change

In this section, we discuss the methodology used to produce the regional indicator of worries about climate change as well as its regional estimates.

3.1 Methodology

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, researchers need to adopt small area estimation methods to produce reliable estimates at sub-national level i.e., regional level (Moretti and Whitworth, 2020).

Small area estimation is a group of statistical approaches increasingly in demand from researchers and policy makers. Indeed, there is a growing need for detailed spatial information. Furthermore, collecting sufficiently large sample data to produce reliable direct estimates[7] of the indicators of interest to smaller geographies involves large costs (Moretti and Whitworth, 2020).

Small area estimation can be performed in different ways (for a review the reader may want to refer to Rao and Molina, 2015). Nonetheless, it is always based on two key steps: i) estimation of 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.

In this paper, we consider a two-step approach following Moretti et al. (2019). First, we create a latent variable measuring worries about climate change at respondent level

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

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.[8] 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 is particularly helpful when Census or administrative auxiliary data are not available for the micro-level units of the population. Indeed, area-level models require aggregated information (Rao and Molina, 2015). 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), and 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 with either the direct or synthetic estimators separately. In fact, whilst the direct estimates are unbiased, they show large variance for those regions with small sample sizes. For 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.

3.2 Results

In this section, we show the results of the composite indicator for the European regions. The Confirmatory Factor Analysis (CFA) model used to estimate the latent variable (worry about climate change) at respondent level shows a good model fit.[9] Given the positive values of the factor loadings[10] between the observed variables and the latent variable estimated from the CFA model, when the indicator takes larger values, this

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

[9]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).

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

denotes more worries about climate change. In this work, we are interested in the mean of this indicator for the European regions.

Table 10 in Appendix B shows the results of the area-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. As mentioned above, 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). As shown in Figure 2 in Appendix B, the Q-Q plot of the area-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 the Spearman's ranking correlation coefficient between the direct and model-based estimates and this returns good results (value equal to 0.94). We show in Figure 4 in Appendix B 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 below 20%, which means that the estimates are of a good quality according to Official Statistics guidelines (see e.g., Spagnolo et al., 2018). For the diagnostics of small area estimates we follow Brown et al. (2001).

Table 2: Regional Estimates of Regions with Stock Exchange Market Only

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 little worried.

We show in Table 2 the small area estimates computed via the EBLUP approach of the regions with an exchange market used in the analysis in Section 4. Once the regional estimates are obtained, these are rescaled between 0 and 1 for comparison and interpretability reasons. In order to rescale them, we use the 'min-max' criterion (Commission et al., 2008; Moretti and Whitworth, 2020). We identify regions with a worry index less or equal than 0.349 as little worried, between 0.350 and 0.649 as worried, and greater or equal than 0.650 as very worried.

In general, we can observe that Europeans do not show very high level of worries about climate change. Among the regions in Table 2, 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 level 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 of that area. Low level of worry can be also observed for the regions of Stockholm and Zurich.

We show in Figure 1 a map of the indicator of worries about climate change for all the European regions (with and without an exchange market). For completeness, we also add the exchange cities to the map. Notice that we locate Iceland and the Canary Islands close to the mainlands in order to produce a smaller map. We can observe an evident heterogeneity of the estimates of the worries indicator between-regions. Overall, 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 particularly high level of worries. 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 high level of worries about the climate transition. We believe that this difference is due to the higher dependence of Finland from 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.

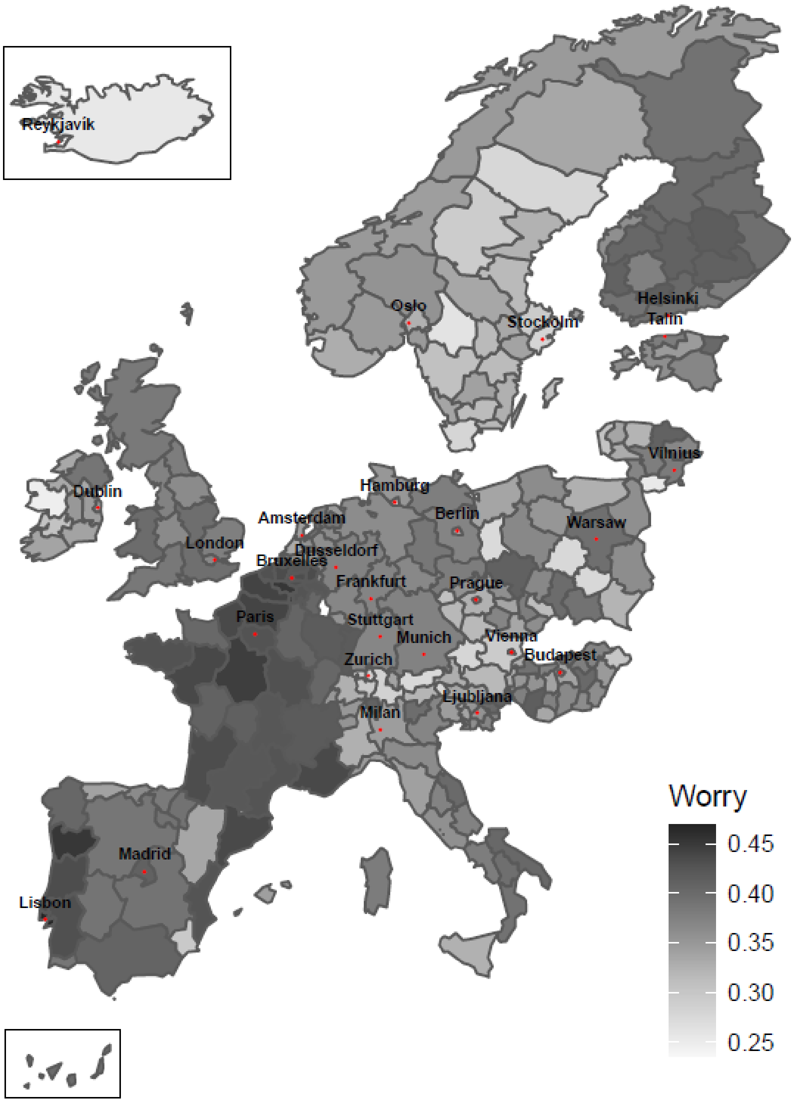

Figure 1: Map of worries about climate change in European regions. Darker colours denote higher worries.

4 Stock pricing and worries about climate change

In this section, we present the econometric methods used to study the carbon risk premium of emission and clean stocks in European regions with different level of worries about climate change. Section 4.2 discusses the results.

4.1 Methodology

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 all the regions, for the little worried regions, and for the worried regions. We identify a region as little worried if it has a worry index lower than 0.35.[11] Successively, we perform regression analysis using both ordinary least square (OLS) and quantile regression (QR) for all the regions, little worried and worried regions. Lastly, we estimate the average treatment effect and quantile treatment effects of being an emission firm on returns for all the regions, little worried and worried regions.

4.1.1 OLS and Quantile regression

As a first step, we estimate the following model using OLS with clustered standard errors for exchange city and QR with bootstrapped standard errors clustered for exchange city:

$$\begin{aligned} r_t =& \alpha + \beta_1 emission + \beta_2 MTB_{t-1} + \beta_3 \log(1 + MktCap_{t-1}) + \\ & \beta_4 \log(1 + CapExp_{t-1}) + \beta_5 ROA_{t-1} + \beta_6 AssetGr_{t-1} + \gamma City + \epsilon_t \end{aligned} \tag{1}$$

where the dependent variable r_t is the cumulative return in 2016. Emission is a dummy variable which is equal to one if the firm 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, and $City$ is a factor variable for exchange city. The exchange city fixed effect allows to control for omitted variable bias due to unobserved heterogeneity such as stringency of local environmental policies.

We decide to estimate Eq. (1) using a QR approach (Koenker and Bassett Jr, 1978) because it allows us to obtain a more detailed picture of the heterogeneity in returns. Moreover, the QR approach provides a more robust and efficient estimation method in

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

comparison to OLS in presence of outliers, and when the error term is not normally distributed (Buchinsky, 1998). OLS regression estimates are presented for completeness. The problem of reverse causality is partially mitigated with the introduction of lagged independent variables. Finally, it is important to stress that the estimates presented in the following sections correspond to associations between stock returns and emission/clean firms rather than estimates of causal effects.

4.1.2 Propensity score matching

In order to have a better understanding of the difference in returns of emission and clean stocks, we complement the previous analysis by estimating the average treatment effect on the treated (ATET). Specifically, we use propensity score matching (PSM) approach to compare average returns of emission and clean stocks with similar characteristics. The 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 are as small as possible. Optimal full matching does not require to specify 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 may be observed and included in the logit regression model. Moreover, in order to find adequate matches, it is necessary to ensure a 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. (1).

4.1.3 Quantile treatment effects

The matching techniques presented so far estimate the average effects of being an emission firm on return. However, since we want to take into account the heterogeneity in returns, we also estimate the quantile treatment effect (QTE) using matching techniques (Firpo, 2007). This method is based on the conditional independence assumption which describes the difference in the quantiles of the outcome variable (returns) for emission and clean stocks without reference to the control variables. Indeed, covariates are used only to estimate the propensity score of the probability of being an emission firm, thus allowing to compare similar stocks. Differently from the standard 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.

4.2 Results

As a first step, we compare the distributions of returns for emission and clean stocks by means of the Fligner-Policello test (results are displayed in Table 3). We can see that for emission stocks, the underlying sample distribution of returns is not the same as the one for clean stocks. The test indicates that emission stocks stochastically dominates clean stocks. Similar conclusions are obtained when we consider only stocks quoted in exchange cities located in regions worried about climate change.

Differently, we find that the distribution of returns of emission and clean stocks is not significantly different for stocks quoted in exchange cities located in regions only little worried about climate change.

After testing for whether emission and clean stocks can have different distribution of returns, we analyze the return differentials of emission and clean stocks using QR and matching techniques.

Table 3: Two-sample Fligner Policello Robust Rank Order Test

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

Notes: The table presents results of the two-sample Fligner Policello robust rank order test on the returns of emission and clean stocks.

4.2.1 Ordinary least squares and Quantile regression

In Table 4, we show the OLS and QR estimates of Eq. (1) for the whole sample. First of all, we can observe that according to both OLS and QR estimates, emission stocks have significantly higher returns than clean stocks. The average emission stock has a cumulative return 7.97 percentage points higher than the average clean stock. Moreover, QR reveals that the return premium of emission stocks increases when considering higher quantiles of the return distribution. Although returns of emission and clean stocks are not significantly different at the 10^{th} percentile, we report a difference of 15.44 percentage points at the 90^{th} percentile.

Tables 5 and 6 report the OLS and QR results for the sub-samples of little worried and worried regions, respectively. First, we notice that in little worried regions emission stocks have significantly higher returns than clean stocks only in high-return stocks (75^{th} and 90^{th} percentiles). Differently, the analysis of worried regions confirms that the return premium of emission stocks increases when considering higher quantiles of the return distribution. This appears to be consistent with the fact that investors located in regions which report low level of worries on climate change on average tend to not price the carbon risk premium. However, investors price the carbon risk premium of high-return stocks which tend to attract higher investor attention.

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). We also observe that the sign of the relationship between size and returns is reversed in lower quantiles. The coefficients of

Table 4: OLS and QR - Returns and emission vs clean stocks

	OLS	q10	q25	q50	q75	q90
emission	0.0797^{**}	0.0130	0.0319^{***}	0.0535^{***}	0.1034^{***}	0.1544^{***}
	(0.0383)	(0.0177)	(0.0116)	(0.0131)	(0.0243)	(0.0431)
MTB	-0.0045^{***}	-0.0011	-0.0028^{*}	-0.0026^{***}	-0.0047^{***}	-0.0071^{***}
	(0.0013)	(0.0011)	(0.0016)	(0.0008)	(0.0009)	(0.0016)
log(1 + MktCap)	-0.0374^{***}	0.0420^{***}	0.0047	-0.0129^{*}	-0.0550^{***}	-0.0887^{***}
	(0.0103)	(0.0118)	(0.0100)	(0.0067)	(0.0100)	(0.0170)
log(1 + CapExp)	-0.0318	-0.0184	0.0161	-0.0124	-0.0312^{**}	-0.0607^{***}
	(0.0225)	(0.0258)	(0.0137)	(0.0104)	(0.0121)	(0.0123)
ROA	0.0011	0.0046^{***}	0.0036^{***}	0.0026^{***}	0.0011	-0.0026^{*}
	(0.0011)	(0.0008)	(0.0013)	(0.0008)	(0.0013)	(0.0015)
AssetGr	-0.0001	-0.0003	-0.0002^{**}	-0.0001^{**}	-0.0001	-0.0002
	(0.0003)	(0.0002)	(0.0001)	(0.0001)	(0.0003)	(0.0005)
Constant	0.0726^{***}	-0.3151^{***}	-0.1541^{***}	0.0089	0.2312^{***}	0.4392^{***}
	(0.0179)	(0.0152)	(0.0197)	(0.0162)	(0.0240)	(0.0405)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2691	2691	2691	2691	2691	2691

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table presents the OLS and QR estimates of Eq. (1). Standard errors are clustered per exchange city, standard errors of the quantile regression models are computed with bootstrap (500 iterations).

the remaining regressors, capital expenditure, ROA and asset growth are on average not significant. QR reveals a positive association between ROA and returns for low-medium quantiles. The evidence on asset growth is mixed: little worried regions report an increasing relation between asset growth and returns. Specifically, asset growth is negatively associated with returns at the 10^{th} percentile and positively associated at the 75^{th} and 90^{th} percentile. Similarly, in worried regions the relationship between asset growth and returns increases when considering higher quantiles of the return distribution. However, the coefficients are always negative.

In sum, what we can conclude from the QR estimates is that emission stocks report a significant premium relative to clean stocks. However, when we focus on regions little worried about climate change, the premium of emission stocks is significant only for high-return stocks.

4.2.2 Propensity Score Matching

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.

Table 5: OLS and QR - Returns and emission vs clean stocks in little worried regions

	OLS	q10	q25	q50	q75	q90
emission	0.0230	0.0359	0.0383	0.0356	0.1071***	0.1083**
	(0.0253)	(0.0605)	(0.0286)	(0.0299)	(0.0243)	(0.0425)
MTB	−0.0043*	−0.0020	−0.0021	−0.0023	−0.0048	−0.0015
	(0.0023)	(0.0052)	(0.0025)	(0.0044)	(0.0030)	(0.0024)
log(1 + MktCap)	−0.0237*	0.0493**	0.0196	−0.0221*	−0.0512***	−0.0967***
	(0.0142)	(0.0191)	(0.0235)	(0.0125)	(0.0111)	(0.0362)
log(1 + CapExp)	−0.0599	−0.1008	−0.0031	−0.0302	−0.0196	−0.0309
	(0.0535)	(0.0624)	(0.0664)	(0.0332)	(0.0316)	(0.0448)
ROA	0.0019	0.0051***	0.0053***	0.0039***	0.0023**	−0.0019
	(0.0018)	(0.0016)	(0.0013)	(0.0012)	(0.0010)	(0.0024)
AssetGr	0.0011***	−0.0013***	−0.0004	0.0003	0.0010***	0.0039***
	(0.0004)	(0.0003)	(0.0006)	(0.0004)	(0.0004)	(0.0006)
Constant	0.0848**	−0.2646***	−0.1716***	0.0490	0.2010***	0.4250***
	(0.0396)	(0.0208)	(0.0458)	(0.0405)	(0.0377)	(0.0619)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	758	758	758	758	758	758

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table presents the OLS and QR estimates of Eq. (1). Standard errors are clustered per exchange city, standard errors of the quantile regression models are computed with bootstrap (500 iterations).

Table 6: OLS and QR - Returns and emission vs clean stocks in worried regions

	OLS	q10	q25	q50	q75	q90
emission	0.1037**	0.0202*	0.0311***	0.0574***	0.0939**	0.1642**
	(0.0468)	(0.0117)	(0.0112)	(0.0203)	(0.0385)	(0.0660)
MTB	−0.0044**	0.0003	−0.0024	−0.0025***	−0.0049***	−0.0078***
	(0.0019)	(0.0010)	(0.0025)	(0.0008)	(0.0018)	(0.0023)
log(1 + MktCap)	−0.0430***	0.0334*	0.0009	−0.0139	−0.0425**	−0.0875***
	(0.0154)	(0.0180)	(0.0085)	(0.0103)	(0.0171)	(0.0306)
log(1 + CapExp)	−0.0185	0.0014	0.0223***	−0.0106**	−0.0318**	−0.0540***
	(0.0162)	(0.0175)	(0.0044)	(0.0048)	(0.0150)	(0.0171)
ROA	0.0007	0.0046***	0.0028*	0.0023***	−0.0001	−0.0027
	(0.0012)	(0.0016)	(0.0017)	(0.0008)	(0.0018)	(0.0018)
AssetGr	−0.0004*	−0.0001	−0.0002***	−0.0002	−0.0002	−0.0003***
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0003)	(0.0001)
Constant	0.1321***	−0.2698***	−0.1265***	0.0431***	0.2803***	0.4365***
	(0.0185)	(0.0236)	(0.0126)	(0.0136)	(0.0231)	(0.0637)
Exchange city FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1933	1933	1933	1933	1933	1933

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. The table presents the OLS and QR estimates of Eq. (1). Standard errors are clustered per exchange city, standard errors of the quantile regression models are computed with bootstrap (500 iterations).

Results regarding the first-step logit regression models are reported in Table 11 in Appendix C. We can observe that capital expenditure and asset growth appears to be the most important variables in determining the likelihood of a stock to be classified as carbon-intensive. On the contrary, 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.

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

	Estimate	Std. Error	Statistic	p-value	Obs
All Regions	0.0843***	0.0276	3.0605	0.0022	2691
Little worried regions	0.0158	0.0492	0.3218	0.7477	758
Worried regions	0.1136***	0.0347	3.2742	0.0011	1933

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, and exchange cities dummies. We adopt the optimal full matching method.

As previously mentioned, 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 6 in Appendix C 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 ATET estimations for the whole sample. The histograms indicate covariate balance.

In Table 7, we report the ATET obtained by PSM. 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.

4.2.3 Quantile Treatment Effect on the Treated

We complement the matching analysis on the average effects employing QTE in order 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 estimates these effects taking into account the unconditional distribution of the outcome variable (i.e., cumulative return).

Table 8 largely confirms previous results that the return premium of emission stocks increases when considering higher quantiles of the return distribution in the whole sample. Similarly, in worried regions, the carbon premium is increasing though it is significant only for medium-high quantiles. In contrast, the difference in return of emission and clean stocks is significant only at the 75^{th} percentile (5% confidence level) in little worried regions.

Since the difference in the carbon premium in worried and little worried regions may be due to differences in local environmental policies (Bolton and Kacperczyk, 2021b), as robustness check we perform the matching considering also the environmental policy stringency (EPS) index developed by the OECD (Botta and Koźluk, 2014). The EPS index is a country-specific and internationally-comparable measure of the stringency of environmental policy. The index measures the extent to which environmental policies put an explicit or implicit price on behaviours that harm the environment. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). For a limited number of countries the index is available until 2015, while for most of the countries the index is available for the period 1990-2012. Among the sampled countries the EPS index is not available for Estonia, Iceland and Lithuania. France, Germany, Italy and the United Kingdom reports the EPS index until 2015 while for the remaining countries the last observation refers to 2012. The EPS index tends to increase over time for all the countries and the variability of the EPS index has decreased over time across European countries. In 2012 the highest EPS index is recorded for the Netherlands (3.625) followed by France (3.567), and the lowest is recorded for Ireland (2.050) followed by Portugal (2.133). Among these countries, the Netherlands and Ireland are classified as little worried and France and Portugal as worried. The Spearman's ranking correlation between the worries index and EPS index is -0.272 meaning that the two variables are not strongly correlated and that environmental policies tend to be more stringent in regions with lower levels of worries. The estimates of the QTEs when we add the EPS index to the set of matching variables are reported in Table 12 in Appendix D. Results are confirmed, this means that the difference in the carbon premium in worried and little worried regions cannot be explained by differences in the stringency of local environmental policies.

Table 8: Quantile Treatment Effect (QTET)- Returns and emission vs clean stocks

	q10	q25	q50	q75	q90	Obs
All regions	0.0527*	0.0227	0.0473***	0.0906***	0.1137*	2691
	(0.0275)	(0.0171)	(0.0151)	(0.0255)	(0.0610)	
Little worried regions	0.0069	0.0436	0.0262	0.1135**	0.0854	758
	(0.0735)	(0.0393)	(0.0329)	(0.0541)	(0.1903)	
Worried regions	0.0352	0.0120	0.0507***	0.0894***	0.1549**	1933
	(0.029)	(0.0204)	(0.0180)	(0.0353)	(0.0682)	

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Treatment variables are emission dummies. The estimated coefficient represents the quantile 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, and exchange cities dummies. Bootstrapped standard errors (500 iterations) are reported in parenthesis.

5 Conclusions

Climate change is a very debated and controversial topic. Despite the agreement in the scientific community on the occurrence and severity of climate change, there are still many who do not accept that the cause of global warming is almost entirely driven by human activity.

This paper develops a regional indicator of worries about climate change using data from the European Social Survey Round 8 (ESS, 2016), and it studies the pricing of emission and clean stocks in worried and little worried European regions. We show that the carbon risk premium tends to be not significant in little worried regions. Differently, returns of emission and clean stocks are significantly different at medium-high quantiles of the return distribution in worried regions. This evidence suggests that public attitudes towards climate change can impact stock pricing. Moreover, investors tend to neglect the carbon risk of low-return stocks.

A limitation of the analysis is that the regional indicator of worries about climate change refers to 2016. As previously discussed, the European Social Survey is a biannual survey, and the topic "Public attitudes to climate change" is present only in round 8 of the survey. However, we argue that although public attitudes towards climate change have certainly changed since 2016, the relationship between worries about climate change and the stock pricing of emission and clean stocks may still hold.

This study has important practical implications. Investors and practitioners can use these results to inform the construction of their investment portfolios. Furthermore, these results are relevant to managers as firms should disclose detailed information on their environmental impact to reduce information asymmetries and improve market efficiency.

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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	1A4c3, 4A,	Fishing (fossil), Enteric Fermentation, Manure management, Rice
	and Plantations	4B, 4C, 4Dr	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 code available from Thomson Reuters Datastream and the matching IPCC category codes which are classified as carbon intensive.

B Small Area Estimation Evaluations

Table 10: Fay-Herriot Area-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: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

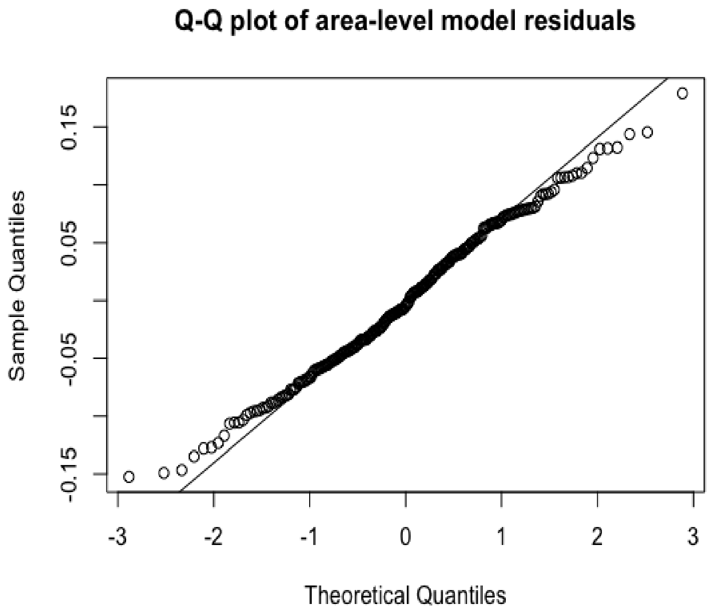

Figure 2: Normal Q-Q plot of area-level residuals.

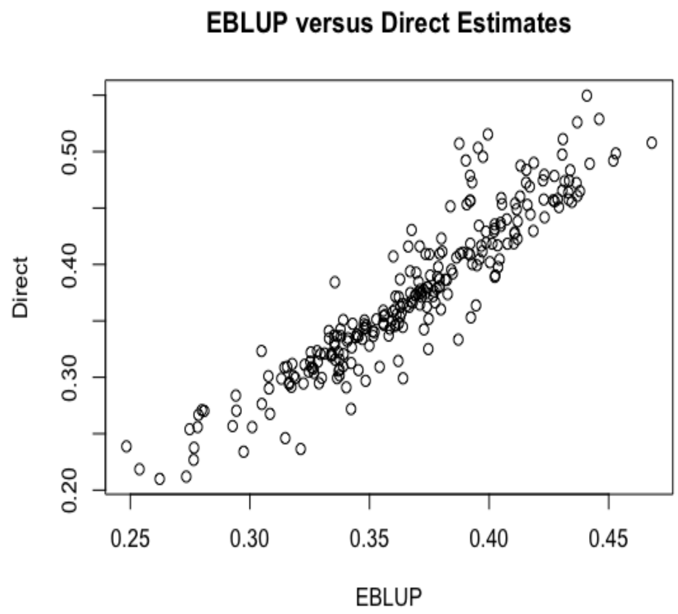

Figure 3: Scatter plot of EBLUP and direct estimates.

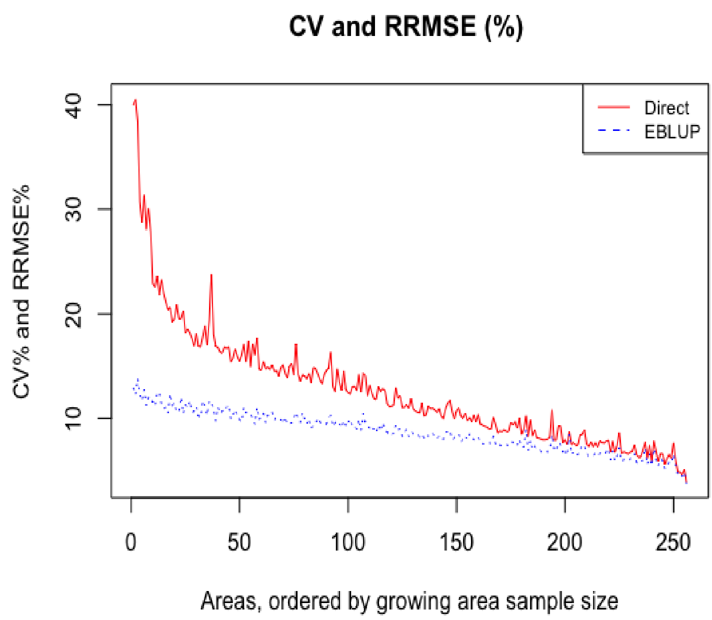

Figure 4: Percentage Coefficient of Variance (CV) for direct estimates and Relative Root Mean Squared Error (RRMSE) for EBLUPs.

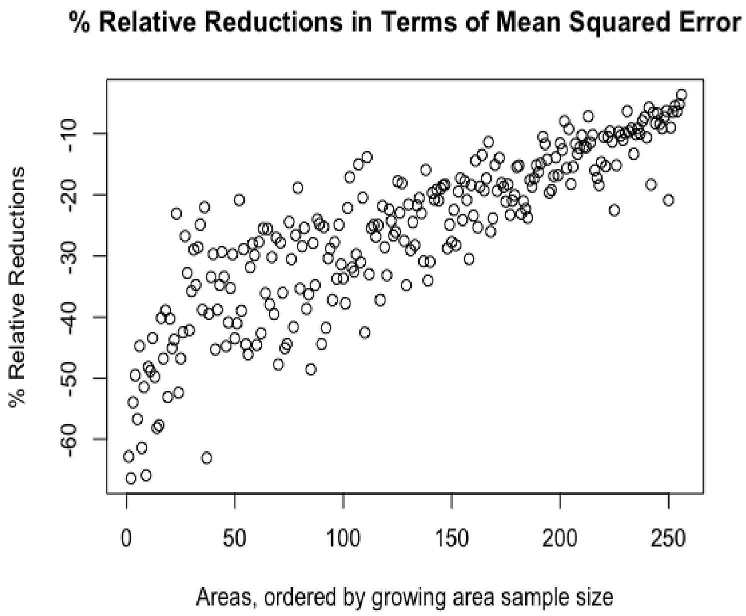

Figure 5: Percentage Relative Reductions in terms of MSE of the EBLUP over the direct estimates.

C Propensity Score Matching

Table 11: First-step of the PSM estimates: Logit model

Regions	All	Little worried	Worried
MTB	−0.0085	0.0147	−0.0279**
	(0.0089)	(0.0118)	(0.0126)
log(1 + MktCap)	−0.0519	−0.0317	−0.0607
	(0.0572)	(0.1024)	(0.0689)
log(1 + CapExp)	0.7008***	0.6153***	0.7434***
	(0.0808)	(0.1497)	(0.0956)
ROA	−0.0041*	−0.0025	−0.0046*
	(0.0023)	(0.0042)	(0.0027)
AssetGr	−0.0063***	−0.0094***	−0.0055***
	(0.0013)	(0.0030)	(0.0014)
Constant	−1.2657***	−1.3040***	−1.6838***
	(0.3100)	(0.3311)	(0.3024)
Exchange city FE	Yes	Yes	Yes
Observations	2691	758	1933

Notes: ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. The regressions include a full set of exchange city dummies which are not reported here for the sake of brevity.

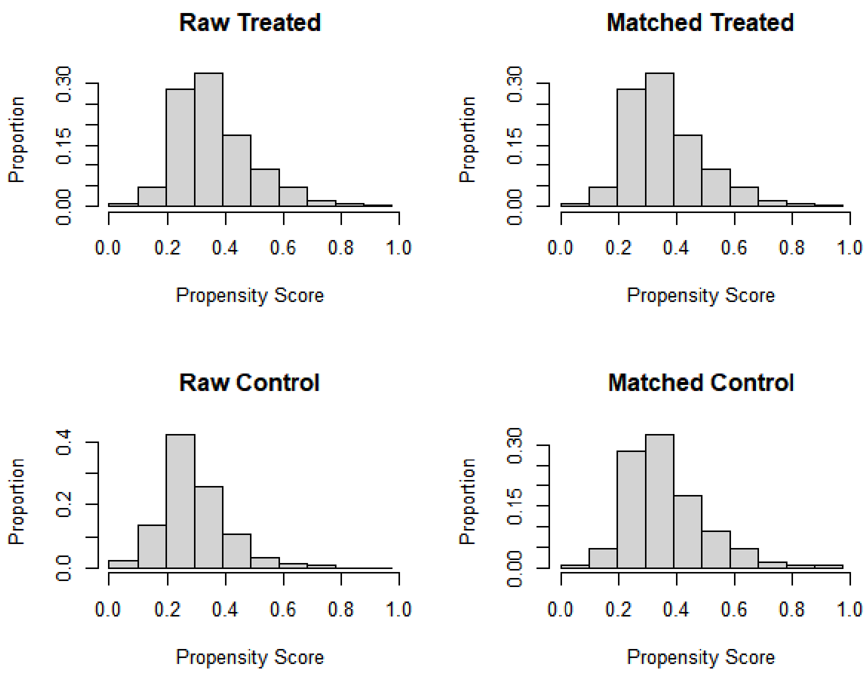

Figure 6: Balance Plot

D Robustness Check - Environmental Policies Stringency

We report here the estimates of the QTEs when we match emission and clean firms according to the following set of variables: market-to-book, market capitalization, capital expenditure per share, ROA, asset growth, exchange city, and environmental policies stringency (EPS) index.

The EPS index developed by the OECD (Botta and Koźluk, 2014) is a country-specific and internationally-comparable measure of the stringency of environmental policy. The index measures the extent to which environmental policies put an explicit or implicit price on behaviours that harm the environment. The index ranges from 0 (not stringent) to 6 (highest degree of stringency). For a limited number of sampled countries the index is available until 2015 (France, Germany, Italy and the United Kingdom), while for most of the countries the index is available for the period 1990-2012. We consider here the EPS index at 2012.

Results are reported in Table 12, note that the difference in the total number of observations is due to the fact that the EPS index is not available for Estonia, Iceland and Lithuania. Findings in section 4.2 are confirmed, this implies that the difference in the carbon premium in worried and little worried regions is not due to differences in the stringency of local environmental policies.

Table 12: Quantile Treatment Effect (QTET)- Returns and emission vs clean stocks

	q10	q25	q50	q75	q90	Obs
All regions	0.0538**	0.0221	0.0473***	0.0890***	0.1130**	2675
	(0.0286)	(0.0181)	(0.0163)	(0.0260)	(0.0603)	
Little worried regions	0.0244	0.0451	0.0289	0.1129*	0.0891	750
	(0.0745)	(0.0359)	(0.0297)	(0.0500)	(0.1628)	
Worried regions	0.0364	0.0119	0.0499***	0.0854**	0.1515**	1925
	(0.0301)	(0.0197)	(0.0190)	(0.0363)	(0.0740)	

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Treatment variables are emission dummies. The estimated coefficient represents the quantile difference in return between emission and clean stocks with similar characteristics. The selection of the control group is based on the matching variables: MTB, market capitalization, capital expenditure per share, ROA, asset growth, exchange cities dummies, and environmental policies stringency. Bootstrapped standard errors (500 iterations) are reported in parenthesis.