IN THE EYE OF CLIMATE CHANGE

AIR POLLUTION AND INVESTOR ATTENTION

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Abstract

Climate change unfolds gradually over decades, making its impacts difficult to perceive in daily life, yet it poses profound challenges for financial markets. Air pollution, by contrast, is acutely salient to individuals and contains components such as black carbon and sulfates that directly contribute to global warming. This paper investigates whether local experiences of abnormal air pollution act as a "wake-up call" that heightens investor attention to climate risks and influences capital allocation. Using the stock market as a natural laboratory, we examine the performance of brown versus green firms through a long–short emissions-minus-clean portfolio, focusing on exchange cities where pollution shocks are most likely to affect investor behavior. We extend the analysis to the European context, where pollution remains a relevant concern with documented cognitive effects. Our study addresses two central questions: (1) does abnormal air pollution increase investors' attention to climate change, and (2) how do local pollution shocks affect the returns of firms with differing climate sensitivities? We contribute to the growing literature on the pricing of climate risks, offering new evidence on how environmental shocks shape the divergence in returns between green and brown firms. This work advances understanding of how environmental salience interacts with financial markets and informs debates on whether climate-friendly firms benefit from their impact on the environment materially.

Keywords

PM2.5, PM10, air pollution, climate change, global warming, investor attention

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1. Introduction

Climate change is among the most pressing global challenges facing the world today. Unlike short-lived shocks, it unfolds gradually over decades, making its impacts difficult to perceive in daily life. It encompasses phenomena such as rising global temperatures, sea-level rise, and an increasing frequency of extreme weather events, while global warming refers specifically to the long-term rise in average temperatures. Despite its slow-moving nature, climate change has profound implications for financial markets, which allocate capital toward or away from firms with varying environmental profiles. The stock market responds not only to fundamentals but also to investor experiences and perceptions, raising the question of whether these experiences can be harnessed to address climate risks through capital allocation.

Air pollution is a critical driver of climate change and, unlike climate change itself, is acutely salient to individuals. Particulate matter (PM2.5 and PM10) is perceptible through visibility, smell, and irritation, and both pollutants contain components such as black carbon, sulfates, and nitrates that contribute directly to global warming (WHO, 2025; Shindell et al., 2012). Thus, air pollution simultaneously degrades local environments and accelerates climate change. Importantly, pollution may act as a "wake-up call" by making environmental risks tangible, potentially shifting investor attention toward climate change.

This raises key questions for the financial market: can local experiences of pollution alter investor perceptions of climate risk, and do these shifts translate into differential pricing of firms with varying climate sensitivities? The stock market provides a natural laboratory to examine these dynamics. In particular, we study whether abnormal pollution events influence the performance of brown versus green firms, as captured by a long–short brown-minus-green portfolio. Our analysis focuses on exchange cities, where local pollution shocks may shape the behavior of investors trading on those exchanges, including blockholders likely located near the exchange.

Although much of the existing literature on pollution and finance has concentrated on countries facing severe air quality challenges, such as China and India, relatively little attention has been devoted to the European context. Yet recent evidence demonstrates that air pollution remains a relevant concern across Europe, with documented effects on cognition and decision-making. Existing finance research has primarily examined pollution's impact on market efficiency and investor behavior, for example, how exposure influences trading performance and biases (Li, Massa, Zhang, and Zhang, 2021; Levy and Yagil, 2011). Far less work has considered pollution as a salient environmental signal that may reallocate capital across firms with differing climate sensitivities. By situating our analysis in Europe, we contribute to filling this gap and provide new insights into how environmental salience interacts with financial markets. Specifically, we address the following two research questions:

1. *Does abnormal air pollution increase investors' attention to climate change?*
2. *How do local experiences of abnormal air pollution affect the stock returns of firms with different climate sensitivities?*

We study 36/33 exchange cities across 32/29 countries in Europe between 2012 and 2024. We study their monthly abnormal levels of PM2.5 and PM10 and their attention to climate change. Then, we examine how abnormal levels of PM2.5 and PM10 affect monthly returns of a long-short emissions-minus-clean (EMC) portfolio. We expect to see heightened attention to climate change during higher abnormal levels of pollution due to the salience of our chosen pollutants, as well as negative returns on the EMC portfolio, in line with existing literature on "green" stocks outperforming "brown" stocks during periods of increased perceived climate risk, increased awareness of climate risk and climate change, greeniums and the costs to "brown" firms due to climate risk and regulation.

This paper builds upon the expanding literature on the pricing of climate risks. Recent work examines whether and how climate risks are reflected in asset prices across different markets, including the stock market (Bolton and Kacperczyk, 2021, 2023), the corporate bond market (Huynh and Xia, 2021), and the real estate market (Baldauf, Garlappi, and Yannelis, 2020). Following the increased salience of climate risks, returns may diverge between "green" and "brown" firms. The central question, whether climate-friendly firms benefit from lower costs of capital (a "greenium") or whether investors demand a premium to hold carbon-intensive firms, remains unresolved. Bolton and Kacperczyk (2021, 2023) document a carbon risk premium, whereas Aswani, Raghunandan, and Rajgopal (2024) find no effect of emissions on stock returns. Other contributions highlight challenges in inference, pointing to noisy ESG ratings (Berg, Kolbel, and Rigobon, 2022) and cross-country heterogeneity (Alves, Krüger, and van Dijk, 2024). We contribute to this literature by examining how climate shocks, specifically shocks to air pollution, affect the pricing of stocks across an emission differential.

Furthermore, our findings connect to research on the role of behavioral biases in how environmental conditions influence investors' decision making. Goetzmann, Kim, Kumar, and Wang (2014) show that cloudier days affect perceptions of mispricing and trading decisions among institutional investors, while Hirshleifer and Shumway (2003) demonstrate that sunshine hours impact stock returns. Similarly, Alok, Kumar, and Wemers (2020) find that institutional investors overreact to large climatic disasters by underweighting disaster-zone stocks, a behavior consistent with salience bias. Inspired by health science evidence that air pollution impairs cognition, Li, Massa, Zhang, and Zhang (2021) document that air pollution intensifies disposition effects among investors.

A more recent strand of literature highlights the financial relevance of air pollution itself. Exposure to poor air quality has been shown to influence investor attention, mood, and risk-taking, generating systematic patterns in trading and returns. Dong, Fisman, Wang, and Xu (2019) provide evidence that analysts exposed to higher pollution during site visits issue more pessimistic earnings forecasts, attributing this to mood effects. Experimental psychology links bad mood to increased risk aversion, while financial economics shows that higher risk aversion leads investors to sell stocks, and lower risk aversion encourages buying (Kamstra, Kramer, and Levi, 2003). Levy and Yagil (2011) further investigate whether these pollution-induced mood effects translate into stock returns. In contrast to this literature, our paper focuses on whether salient pollution experiences can draw investor attention to climate change and thereby affect the pricing of brown versus green stocks.

While Liu, Kang, Guo, and Sun (2021) study how pollution-induced changes in investor attention toward specific firms translate into stock price movements, our analysis considers a broader information channel. We show that air pollution does not necessarily heighten attention to climate risks nor consistently generate return effects. Consistent with this distinction, Fisman, Ghosh, Sarkar, and Zhang (2023) find that increased accessibility to air-quality information, rather than local pollution exposure itself, shifts investment away from brown industries. Taken together, these findings suggest that pollution episodes do not reliably raise climate attention or produce return responses, and our paper provides new insights into the limits of pollution's effect in financial markets.

Finally, our work is closely related to Choi, Gao, and Jiang (2020), who examine how updated beliefs about global warming following local experiences of abnormally warm temperatures are reflected in asset prices and trading behavior. This is consistent with related work in behavioral economics, showing that personal experiences with global warming increase perceptions of climate risk (Zaval et al., 2014; Broomell, Budescu, and Por, 2015). We view our study as complementary, focusing instead on whether extreme local air pollution alerts investors to climate change and how such experiences affect stock market outcomes. Understanding when and how investors respond to local air pollution is important, as it can inform the design of more effective strategies to mitigate climate change by taking air pollution into account. Indeed, there is growing recognition in policymaking that air pollution and climate change are deeply interconnected and should be addressed jointly rather than in isolation.

The structure of this paper is as follows. Section 2 introduces hypotheses and methodology. Section 3 describes data collection and variable construction. Section 4 presents the empirical results. Section 5 highlights key findings and limitations. Section 6 concludes.

2. Hypotheses & Methodology

We follow the methodology used by Choi, Gao, and Jiang in their article *Attention to Global Warming* (2020). While they study the stock market implications of temperature shocks, this study investigates the impact of air pollution shocks. In particular, we would like to identify investor reaction to climate change in times of unusually high local air pollution. In fact, research shows that air pollution and climate change are closely linked (see e.g., Ramanathan and Carmichael, 2008; Shindell et al., 2012). However, comparatively few empirical studies investigate whether and how the public perceives air pollution as a driver of climate change.

We further deviate from Choi et al. (2020), who study several exchange cities across the world. An advantage of using an international setting is that the researchers are able to estimate people's opinions about temperature shocks in different parts of the world, and examine how the general public realizes and responds to such impacts of climate change. Given that climate change is a global phenomenon, understanding collective beliefs and actions across the world are important determinants of the efficacy of climate policies and campaigns.

In this study, we limit our focus to 36/33 cities across 32/29 countries in Europe. We examine the collective beliefs and actions of a large proportion of the European public. This means a slightly narrowed focus from that of Choi et al. (2020). While they

investigate global market reactions to local temperature shocks, we study whether markets with relatively strong environmental regulation recognize the impact of air pollution shocks on climate change. In Europe, research on the financial implications of air pollution remains limited. However, given Europe's substantial geographical variation and differences in national regulatory frameworks compared to most of the Asian countries studied in prior literature, a European-focused investigation offers valuable insights into investor behavior under environmental stress.

2.1 Air pollution and investor attention

Investor reaction to climate change is first measured by an exchange city's Google Search Volume Index (SVI) of the topic "global warming", which proxies for the local people's attention to climate change. The idea follows Da, Engelberg, and Gao (2011), who use SVI of stock tickers to study investor attention. Given an understanding of the interrelationship between air pollution and climate change, the appearance of abnormal levels of air pollution may induce investors to consider climate change, thus searching for more details in, for instance, Google. Related literature suggests that people adapt beliefs on their experiences of air pollution (Li, Massa, Zhang, and Zhang, 2021; Liu, Kang, Guo, and Sun, 2021; Dong, Fisman, Wang, and Xu, 2019). Chang, Huang, and Wang (2018) document a significant effect of daily air pollution levels on the decision to purchase or cancel health insurance, acknowledging the increased perceptions of health risks following air pollution episodes. In addition, the study of Fisman, Ghosh, Sarkar, and Zhang (2023) shows that releasing information about the local air quality leads retail investors in China to reduce their investments in brown stocks, with particularly pronounced effects amongst younger investors who tend to be more sensitive to climate concerns. Their results provide support for the view that salience of air pollution conditions updates investors' beliefs about climate risks, thereby increasing investor preferences towards green investments. In our case, abnormal air pollution may serve as a signal of deteriorating environmental conditions and, by extension, poor local performance with respect to climate-related objectives. Such shocks can prompt investors to reassess the likelihood and financial relevance of climate risks, thereby increasing their demand for climate-related information. This mechanism would align with evidence that salient environmental conditions update beliefs and redirect attention (Choi et al., 2020). Consequently, air pollution shocks are expected to trigger greater information acquisition about climate change, as reflected in elevated search activity. Contingent on this analysis, we test the following hypothesis:

(i) Abnormal air pollution increases investors' attention to climate change.

2.2 Air pollution and stock return

Next, we examine the reaction of investors in the stock market. A growing body of literature shows that air pollution could affect stock markets through multiple channels. First, air pollution could trigger a number of physiological and psychological changes in investors. A medical study has proven that exposure to urban air pollutants could trigger increases in bodily cortisol levels (Tomei et al., 2003). Individuals with higher bodily cortisol levels are less likely to engage in risk-taking behavior (Rosenblitt et al., 2001). Hence, air pollution could increase investors' risk aversion, making individual investors

buy fewer stocks (Lepori, 2016; Wu and Lu, 2020). Moreover, higher air pollution levels are documented to make fund managers pessimistic, finally affecting their trading behavior and the stock prices of their shareholdings (Wu et al., 2020). These findings suggest that air pollution may impact investor behavior and thereby the stock market through mechanisms unrelated to fundamentals, including cognitive performance, preferences, and affect.

Second, periods of abnormally high air pollution may heighten the salience of environmental risks for investors. Salience refers to the tendency for an individual's attention to be drawn to particular prominent features, which then exert a disproportionate influence on decision-making (Chang, Huang, & Wang, 2018).There is a substantial body of empirical studies that finds evidence of salience in the field (e.g., Bordalo et al., 2013, 2014; Koszegi and Szeidl, 2013). Choi et al. (2020) conjectures that retail investors have limited attention and are therefore more likely to react to *abnormal* weather events. They discover that people revise their climate change beliefs upward when the local temperature is abnormally warm, and conclude that unusually warm weather is a salient event that attracts attention from and affects behavior of individual investors. Similarly, unusually high levels of air pollution may also attract investor attention. On recognizing the impact of air pollution on global warming and thereby the implied risk of climate change, socially responsible investors may avoid environmentally unfriendly firms, in line with how sin stocks are shunned by norm-constrained investors (Hong and Kacperczyk 2009).

This suggests that air pollution may affect stock return through its impact on investors' preferences toward green stocks (Fisman et al., 2023). Indeed, Pástor, Stambaugh, and Taylor (2022) find that during periods of unexpected concerns about climate change, green firms' stock prices rise while brown firms' prices fall, due to increased investor demand for greener firms, or increased customer demand for greener products. As a driver of climate change, air pollution might as well contribute to climate change concerns. In addition, when air pollution is unusually high and the risks of climate change are more salient or top of mind, investors may update their own valuation of firms.

Investors may believe that the future cash flows of climate-sensitive firms are negatively impacted because climate change can disrupt production processes, increase the costs associated with future emissions, or lead to stricter emissions regulations. For example, fossil fuel firms are particularly vulnerable to carbon pricing policies (Krueger, Sautner, & Starks, 2020). The introduction (or anticipation) of carbon pricing can change cash-flow expectations and alter expected returns (Jaccard, Kockerols, and Schüler, 2025). Liu, Kang, Guo, and Sun (2021) finds that air pollution reduces the stock prices of polluting companies listed on China's A-share market, which is known to be policy-driven. They argue one potential mechanism is that air pollution can force the government to introduce environmental policies which may influence investors' strategies.

In order to understand the role of investors' attention to climate change on the stock market's reactions to air pollution, we study monthly size-adjusted stock returns of firms with different sensitivities to climate change under abnormally high air pollution levels. If investors start to recognize the impact of climate change through air pollution shocks on financial markets, they may buy firms with low climate sensitivity and sell those with high climate sensitivity, leading a long-short portfolio of high-low

sensitivity firms to earn negative returns. Based on our analysis, we test the following hypothesis:

(ii) Air pollution directly leads to the underperformance of brown stocks relative to green stocks.

3. Data and Variables

3.1 Data collection

Air pollution

We obtain daily and hourly measures of two pollutants, PM2.5 and PM10, from the European Environment Agency (EEA) Air Quality Download Service[1] and from corresponding with EEA Spatial Data Infrastructure. The input data used in building these daily observations contain air quality records from over 83,000 air quality monitoring stations across Europe since 2002, with significantly lower coverage dating back to 1999 in some cities. By using the location coordinates, we identify air quality monitors in the city of 36 European stock exchanges. As a benchmark, Choi et al. (2020) study 74 cities globally that have major stock exchanges.

The sample obtained covers the period from January 1, 2002 to 31 December, 2024. Estimating abnormal air pollution requires 10 years of data before the actual test period, therefore our main test period is restricted to 2012 to 2024, which differs from the test period from 2001 to 2017 used by Choi et al. (2020). These two time periods differ mainly in that the 2001–2017 period captures a stage during which climate change was increasingly discussed but still transitioning into a financial concern, whereas the 2012–2024 period reflects a stage where climate change is already widely perceived as a global challenge, with investors, regulators, and firms responding to rising expectations around environmental performance. Several studies document an increasing awareness of risks and concerns tied to climate change after the Paris Agreement in 2015 (see, e.g., Bolton and Kacperczyk, 2021; Pástor, Stambaugh, Taylor, 2022). Given this is within our test period, it can potentially affect our results. One important concern about including 2020–2022 in the test period is that it overlaps with large-scale macroeconomic events, the most notable being the COVID-19 pandemic in 2020 and the Russia-Ukraine war in 2022. This raises concerns about confounding events, with the risk that the estimated effect of air pollution shocks may be influenced by overlapping structural shocks from the COVID-19 pandemic and the Russia-Ukraine war. To account for this, we use year-month fixed effects. Time-fixed effects can remove the effects of confounding events that are constant across all units at a specific time point, such as a national economic recession or a pandemic. By including time fixed effects, we control for any shocks or trends that affect all observations at a particular time, ensuring that any remaining effects are due to changes that vary within units over time.

The choice of pollutants is motivated by the findings of Chang et al. (2018). They show that air pollution, measured by PM2.5, significantly influences individuals' decision to purchase or cancel health insurance, providing evidence for projection bias

[1] https://www.eea.europa.eu/en

and salience. In our analysis, we examine the perceived salience of air pollution and its relationship to climate change. Therefore, in our analysis we use PM2.5, and PM10 in additional tests, known to be salient as previously described.

However, studying the salience of air pollution for financial markets would ideally take into account the physical location of the traders whose decisions drive stock prices and their exposure to air pollution. A deviation from the ideal dataset would introduce the possibility that any effect of local air pollution shocks on the relative performance of high-emission versus low-emission shocks may be more difficult to detect, as trading activity from individuals located outside the affected area may attenuate the results. Since we cannot observe the stock market traders' actual locations nor their direct air pollution exposure, we must assume that a substantial fraction of trading activity, particularly the activity that influences stock prices, is undertaken by traders physically located in or near the exchange city. This is reasonable given that exchange cities are important cities where many investors are located, and prices are affected by domestic investors (Chan, Hameed, and Lau, 2003), who most likely are exposed to local environmental conditions. We therefore study the impacts of shifts in environmental conditions in European exchange cities, following the approach of Choi et al. (2020).

Temperature

Similar to Choi et al. (2020), we collect daily temperature data from a dataset provided by the National Climatic Data Center (NCDC)[2], specifically Integrated Surface Data (ISD). This data collects weather records from more than 9,000 stations across the world starting in 1973. ISD is transformed into Global Surface Summary of Day Data (GSSD). We use this GSSD, apply the location coordinates, and select the weather stations closest to the address of the exchange. From this source, we assemble a continuous series of daily temperature data for the period 2002 – 2024.

Search Volume Index by Google

We collect data regarding internet search activity from Google Trends, which offers a "Search Volume Index" or (SVI). We specifically collect data on the topic "global warming".[3] While "topics" adjust for spelling errors and searches across languages, search terms do not. Google's algorithms are able to categorize different search terms with similar or same meanings in the same topic.[4] Therefore, we use data on search topics. The monthly SVI in each of the 36 European locations of interest is downloaded from 2012 to 2024. We examine topic search data at both levels, exchange city and exchange country. The exception is countries where topic data is only available at the exchange country level.[5] In those cases, we use the country-level SVI to approximate

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[2] https://www.ncei.noaa.gov/

[3] To ensure we cover all relevant searches, we also looked at the monthly topic data for the topic "climate change". Traffic for this topic is almost insignificant, and especially much less than for topic "global warming" in the initial sample years. Now, both topics appear to have high correlation. For the rest of the paper, SVI refers to the topic "global warming".

[4] Google Search blog offers more details: https://search.googleblog.com/2013/12/an-easier-way-to-explore-topics-and.html.

[5] The countries with only country-level SVI include: Bosnia Herzegovina, Bulgaria, Cyprus, Denmark, Estonia, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Lithuania, Luxembourg, Malta, Netherlands, Poland, Serbia, Slovak Republic, Slovenia, Spain, Sweden, and United Kingdom.

the exchange city-level SVI, assuming that most of a country's search frequency in Google is mainly driven by its largest exchange city. This is in line with the method of Choi et al. (2020).

Similar to SVI, we are limited to country-level measures of environmental regulation, news coverage and news sentiment. We use these country-level measures to proxy for the local perception of these conditions by the people in the exchange cities of the country. This assumes, for instance, that climate news articles or in one city might still raise attention to and concern about the climate among people in other cities. In countries with greater land area, we expect inhabitants to be more spread and less densely populated, therefore our assumption will hold weaker. In larger countries where the population is more dispersed, this assumption will be weaker. However, as most exchange cities are important cities with high populations, concentrated capital, and extensive media coverage (Choi et al., 2020), it may remain plausible to assume that the local activity in the exchange cities is captured by the overall national signals. Although deviations from the ideal city-level datasets might introduce measurement error, the country-level proxies should still capture meaningful variation in the local public attention and concern.

News media

We use Global Data on Events, Location, and Tone (GDELT) to collect country-level data that assigns scores to news coverage and news tone across 36 countries.[6] The GDELT project is considered one of the largest and most comprehensive open databases, integrating real-time translation of media from over 100 languages. The underlying news sources cover over 1,000 outlets, such as BBC, Corriere della Sera, and Aftonbladet. These outlets are highly visible to market participants within each country, making them well suited to capturing the prominence of climate change–related discussion that investors can access at minimal cost. Additionally, GDELT evaluates the tone of news coverage using advanced sentiment lexicons that classify positively and negatively charged language. By inferring sentiment directly from textual features rather than relying on a fixed, pre-defined emotion dictionary, this methodology helps limit prediction bias stemming from subjective judgments (Schumaker et al., 2012).

There are two types of databases in GDELT, the Global Knowledge Graph (GKG) and the Events database. In this paper, we use the GKG database to extract daily European news articles containing the key words in the Climate Change Vocabulary (CCV) constructed by Engle, Giglio, Kelly, Lee, and Stroebel (2020), their respective country of publication, and the average tone score of these climate change news published in the country for a given day. The CCV is a compilation of terms and their corresponding frequencies with which they appear in an aggregated corpus of seventy-four authoritative climate change texts produced by governmental agencies and research institutions.[7] However, using GDELT in this way presents a limitation. Terms that are prevalent across several news articles, as well as those that occur only rarely within a particular article, are less informative about the content of an individual article. Rather, the most informative terms are those that appear infrequently overall across news articles but frequently within a specific article under consideration (Engle et al.,

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[6] https://www.gdeltproject.org/ Research using GDELT includes work by Shen et al. (2022), Casanova, Ortiz, Rodrigo, Xia, and Iglesias (2017), and Elshendy and Colladon (2017).

[7] Figure 1 (Appendix) contains the Climate Change Vocabulary (CCV). *Hedging Climate Change News* (Engle et al., 2020) explains the construction of the Vocabulary. https://doi.org/10.1093/rfs/hhz072

2020; Gentzkow et al., 2018). As we cannot observe the frequency with which our keywords appear, news articles that include the related keywords but do not substantively focus on climate change may be mistakenly counted as climate change coverage, potentially inflating the daily counts and introducing noise into the constructed indices.

To reduce this risk, we restrict our sample to news articles containing only the subset of the CCV terms that appear most frequently in the authoritative climate change texts.[8] These high-frequency terms are more likely to be core and topic-defining. While this approach does not eliminate misclassification entirely, it narrows the set of included articles to those more plausibly centered on climate-related content. Using the GKG database, we also collect the daily number, country of publication, and average tone score of European news articles containing the keyword "air pollution", which is not included in the CCV of Engle et al. (2020).

Using news media coverage as a measure of the public's attention to and concern about climate change relies on the assumption that discussions about climate change or air pollution become more frequent when the perceived climate risk rises. The news media coverage measure implicitly treats the absence of climate change news as indicative of good news. Although this assumption is plausible, it may lead to measurement error by conflating discussions of positive climate news (e.g., news about new mitigation technologies) with increases in the perceived climate risk (Engle et al., 2020).

To address this possible concern, we therefore collect the average tone score of the news articles published on a given day, inspired by Engle et al. (2020). In constructing climate risk hedge portfolios, Engle et al. (2020) quantify climate risk using two news-based indices, one of which is specifically intended to capture negative climate change news. Our data set differs from that of Engle et al. (2020), whose methodology is used in the construction of our sentiment measure for the news articles on climate change and air pollution, in two ways. First, Engle et al. (2020) obtain news data through the data analytics vendor Crimson Hexagon, which relies on news sources including The Wall Street Journal, The New York Times, and The Washington Post. We rely on the GKG database provided by GDELT, with coverage beyond top outlets. Second, the sentiment index of Engle et al. (2020) is constructed as the share of articles published on a given day that have been assigned to the topic "climate change" and classified as exhibiting "negative sentiment". With GDELT, we similarly observe the sentiment of individual news articles, only the aggregate tone of articles published on the same day. The article tone, ranging between –100 and 100, is a score defined as from the difference between positive and negative words divided by total words (Shen, Xia, Shuai, and Gao, 2022). Accordingly, a limitation of the average tone measure is that a tone score of zero may reflect either neutral language or the aggregation of strongly positive and strongly negative words that offset one another in the articles.

Stock and company information

Information on stock price, market capitalization, industry classification, and the exchange city of listing is obtained from Thomson Reuters DataStream, which provides coverage of over 100,000 equities across nearly 200 countries from 1980 onward. We collect information for stocks listed on European stock exchanges, as defined by

[8] We use Climate, Change, Carbon, Climate change, Emissions, and Greenhouse as the climate change keywords.

DataStream. The list of the European exchange cities and countries of these stock exchanges can be found in Table 2A in the Appendix.

In order to account for the companies' differences in sensitivity to climate change, we use proxies for their carbon emission levels. Similar to Choi et al. (2020), we use industries as defined by the Intergovernmental Panel on Climate Change (IPCC) (Krey et al. 2014). The IPCC serves as the foremost international authority on climate change. According to the IPCC, the following five industry sectors are identified as the largest carbon emitters: Energy, Transport, Buildings, Industry (chemicals and metals), and Agriculture, Forestry, and Other Land Use (AFOLU). IPCC breaks down each sector further into subcategories. We manually match subcategories with Datastream industry subsector names.[9] If a firm's DataStream industry name is matched to one of the five aforementioned industries, it is classified as a high-emission firm. Otherwise, a firm is classified as a low-emission firm. While the DataStream industry subsector names highly resemble the ones used by Choi et al. (2020) in their firm classification, some of the industry names we obtain are more granular. For instance, while obtaining the industry subsector name "Non-ferrous Metals" as Choi et al. (2020), we also obtain "Platinum and Precious Metals", which we group under non-ferrous metals.

Moreover, we follow Choi et al. (2020) in using MSCI ESG Ratings to access firm-level carbon emission scores. The carbon emission scores are industry adjusted, enabling comparisons across industries. Reported on a scale from 0 to 10 for publicly listed firms only, a higher carbon emission score indicates stronger ESG performance. Firms assigned MSCI carbon emission scores between 0 and 3 (7 and 10) in the previous calendar year are categorized as high- (low-) emission firms. We consider the previous calendar year because investors do not have the MSCI emission scores for the current year, with the latest scores being based on the previous year's firm actions. The data coverage on MSCI carbon emission scores is limited to 2012–2022, and only a smaller subset of stocks listed on European exchanges. Unless otherwise stated, firms are classified into high or low emission based on the IPCC definitions throughout the paper.

Environmental regulation

To proxy for the stringency of environmental regulation, we employ the OECD Environmental Policy Stringency (EPS) Index, a widely adopted policy analysis measure developed by Botta and Koźluk (2014). The choice of proxy is based on the conviction that it is, to date, the least imperfect proxy for environmental regulation stringency in the context of cross-country comparisons over relatively long periods in Europe. Following its revision in 2022, the index provides annual measures of environmental policy stringency for the period 1990–2020 across 40 countries, encompassing 13 environmental policy instruments focusing on primarily climate change and air pollution mitigation. These instruments are organized into three composite sub-indices: market-based measures such as taxation on CO_2, NOx, SOx, and diesel fuel, CO2 and renewable energy certificates, regulatory, non-market instruments such as emission limit standards for NOx, SOx, and particulate matter, as well as limits on sulphur content in diesel, and lastly technology-oriented policies, measured through public R&D spending and support for the deployment of solar and wind energy. Index

[9] For example, Coal (DataStream ICB subsector code = 60101040), Gold Mining (DataStream ICB code = Gold Mining), and General Mining (DataStream ICB code = 55102000) are matched with Mining and Quarrying (IPCC code = 1A2f4).

values range from 0, indicating the least stringent policy environment, to 6, indicating the most stringent.

We collect the EPS index between 2012 and 2020 for the 22 European countries available. Whereas Choi et al. (2020) rely on the Environmental Regulatory Regime Index (ERRI) developed by Esty and Porter (2001), we deviate from this choice because ERRI is static and therefore less likely to capture recent evolution of environmental policy stringency, particularly in areas related to climate change and air pollution mitigation.

3.2 Variable construction

Dependent variables

Google DSVI

To capture changes in attention, we follow Choi et al. (2020) in calculating the log monthly change in the Google Search Volume Index, *DSVI*. *DSVI* is computed as the residuals from the regression of the log change in the monthly *SVI* on month-of-year dummy variables:

$$DSVI_{it} = [\Delta ln(SVI_{it}) - \overline{\Delta ln(SVI)_m}] \times 100 \qquad \text{Eq.(1)}$$

where SVI_{it} is the *SVI* for city *i* in month *t*, $\Delta ln(SVI_{it})$ is the monthly log change in *SVI*, *m* is the calendar month (1–12), and $\overline{\Delta ln(SVI)_m}$ is the average log change for that month across years. This approach accounts for potential seasonal patterns in the Google *SVI* of the topic "global warming". We winsorize the *DSVI* values at the top and bottom 2.5% tails to avoid the impacts of extreme values on estimation results. These *DSVI* values are then scaled by a factor of 100 to allow interpretation of its magnitude. We denote the city-level *DSVI* as *DSVI(city)*. We also obtain the country-level *DSVI*, denoted *DSVI(country)*, using Eq.(1) with the SVI_{it} representing country *i* in month *t*. In countries with more than one stock exchange, we select the exchange city of the stock exchange with the highest aggregate market capitalization.

Portfolio return

We examine stock market reaction by first computing the raw stock return, *R*, as the change in stock price, *P*, over each month *t* for a given stock *j*:

$$R_{jt} = \frac{P_{jt} - P_{jt-1}}{P_{jt-1}} \qquad \text{Eq.(2)}$$

The literature notes that DataStream may suffer from data errors. To account for potential data errors, we follow Choi et al. (2020), Hou, Karolyi, and Kho (2011), and Ince and Porter (2006) in excluding monthly raw stock returns exceeding 300% that reversed within one month, as well as zero monthly returns, which arise because DataStream repeats the last available stock price for delisted firms. The remaining raw stock returns are winsorized at the upper and lower 2.5% tails within each exchange-month combination. We then use the natural logarithm of the raw return and compute the size-adjusted return as the raw return minus the average raw return of stocks in the same size quintile within the same exchange and month. Finally, following

IPCC definitions, we construct two city-level portfolios. Portfolio $EMISSION_i$ comprises all high-emission firms located in city i, while portfolio $CLEAN_i$ includes the remaining low-emission firms in that city. All portfolios are constructed using equal weights and value weights. The portfolio return, expressed in percentage term, is computed as the average raw or size-adjusted return of stocks in each portfolio in month t, using equal or value weights. The average size-adjusted returns of stocks included in the portfolios $EMISSION_i$ and $CLEAN_i$ are denoted as *RET(EMISSION) and RET(CLEAN)*, respectively. The corresponding long-short portfolio, EMC_i ($EMISSION_i$ minus $CLEAN_i$), is constructed by taking a long position in $EMISSION_i$ and a short position in $CLEAN_i$. We then calculate the raw and size-adjusted *EMC* portfolio return, denoted *EMC(raw)* and *EMC(adj)*, respectively.

Size-adjusted returns are used as opposed to only raw returns to account for market capitalization. In replicating Choi et al. (2020), we observe that their measure is used to estimate a quantity similar to a quintile-based excess return. This helps scale potentially large raw numbers into meaningful "excess returns" that reflect the true performance of the firm beyond just what its firm size drives. In addition, this helps evaluate a firm's performance by removing the effect of its size, allowing for a more direct comparison of returns between companies of different market capitalizations.

Independent variables

Abnormal air pollution

In this paper, we extend the study of Choi et al. (2020) by examining air pollution as the primary independent variable. Adopting their decomposition framework for local temperature, we similarly decompose local air pollution into components capturing predictable trends, seasonal variation, and abnormal fluctuations. For each city i in month t, we compute monthly local air pollution, denoted AP, as the average of daily average pollution levels[10], and then define:

$$AP_{it} = Avg_AP_{it} + Mon_AP_{it} + Ab_AP_{it} \qquad \text{Eq.(3)}$$

where Avg_AP_{it} denotes the average level of monthly local air pollution in city i over the 120 months preceding month t, Mon_AP_{it} denotes the average monthly deviation in local air pollution from the city's average (defined as the difference between the average air pollution in city i during the same month of the year over the previous 10 years and Avg_AP_{it}), and the remainder, Ab_AP_{it}, denotes the abnormal air pollution in city i during month t. Calculated this way, a city's abnormal air pollution will represent a new experience for the people in the city, thus more likely to represent a salient event.

Abnormal temperature

There is a risk for potential endogeneity between the monthly abnormal air pollution and the differential in performance of high-emission and low-emission stocks. The endogeneity may arise if there are omitted variables that simultaneously affect both air pollution and stock return. Including the monthly abnormal temperature in city i, Ab_Temp_{it} as a control variable may partially mitigate endogeneity (see Ardia et al.,

[10] When only hourly pollution observations are available, we first aggregate them to daily values and subsequently to monthly values.

2022), given the positive impact of extreme heat on air pollution (WMO, 2023) (Harvard, 2025) and a documented effect of temperature shocks on the financial market. Hirshleifer and Shumway (2003) find that sunshine is strongly correlated with stock returns, Addoum, Ng, and Ortiz-Bobea (2023) find that high temperature shocks negatively affect companies' earnings, and Choi et al. (2020) find that carbon-intensive firms underperform less carbon-intensive firms during periods of unusually warm weather. As with Ab_AP_{it} in Eq.(3), we decompose monthly local temperature into three components: the average monthly temperature in city i over the 120 months preceding month t, the average monthly deviation in local temperature from the city's average, and the abnormal monthly temperature in city i, denoted Ab_Temp_{it}.

Environmental policy stringency

Following Choi et al. (2020), we construct a measure for the quality of the environmental regulatory system. Based on the OECD Environmental Policy Stringency (EPS) Index, we assign each country an EPS score, denoted *Reg_Score*, and construct a dummy variable of EPS, *Reg_High*, to denote countries whose EPS score is above 3.5 on a range between 0 and 6. The annual country-level *Reg_Score* and *Reg_High* are used as proxies for the EPS score in month t in the year of *Reg_Score* for the largest city i by market cap in country of *Reg_Score*, denoted Reg_Score_{it} and the dummy variable taking the value of one whose EPS score is above 3.5, denoted Reg_High_{it}. *Reg_High* captures countries, within each month, with an above-average environmental regulatory system.

Climate change news coverage

Inspired by Pástor, Stambaugh, Taylor (2022) and Ardia, Bluteau, Boudt, and Inghelbrecht (2022), we include a regression analysis with interaction effects taking into account variables contributing to climate change concern. This represents an extension of Choi et al. (2020), who only focus on investor attention in relation to local abnormal temperature. Because of high public awareness about climate change in Europe (European Commission, 2025), considering the extent to which climate change information affects investors' reaction to local abnormal air pollution will positively contribute to our paper and add valuable insights.

We use the total number of daily news articles on climate change keywords provided by GDELT. In order to measure shocks in the quantity of climate change news, we average the daily values for the total number of news articles containing chosen keywords to the monthly level, and then construct values of the variable $ClimateNewsCoverageChange_{it}$, as the log changes in the total number of climate change news articles published in country i in month t, adjusted for seasonality, using Eq.(1). There are two advantages of using Eq.(1) to measure shocks in quantity of climate change news: (i) subtracting the log change for the month-of-year adjusts for seasonality and removes variations in number of climate change news articles that may occur due to seasonal factors or cyclic events (Shanahan, 2017), and (ii) calculating the log change removes the potential persistence in the article news count (Shen et al., 2022). This allows the *ClimateNewsCoverageChange* values to exclusively capture unexpected shocks to climate change news.

In line with research (Shanahan, 2017), we assume that climate change discussions in news media increase around climate-relevant events such as heatwaves, climate commitments and climate summits. With increased climate coverage, it is also

reasonable to assume an increased level of concern about the climate. Prior research documents the significant role of news media in shaping public awareness of and perceptions toward environmental issues (Schoenfeld et al., 1979; Slovic, 1986; Boykoff and Boykoff, 2007; Sampei and Aoyagi-Usui, 2009; Hale, 2010). Media influence public perceptions through several channels, including the informational content conveyed in news reporting, the intensity of media coverage devoted to a topic, and the emotional tone embedded in that coverage. Consistent with Ardia et al. (2022), we argue that these dimensions together make the news-based measure a meaningful proxy for shifts in climate change concern. This approach is further supported by the framing theory of Chong and Druckman (2007), which emphasizes that the manner in which information is presented influences individual attitudes toward a subject. Accordingly, the level of climate change concern portrayed in news media is expected to directly affect public concern regarding climate change. In an ideal scenario, we would want to measure the level of investors' concern caused by the informational content of climate change news articles to better capture climate change concerns due to media coverage on the subject. Ardia et al. (2022) design a score to measure such concern by combining the levels of discussion about consequences of climate events and the negativity in each news article with the subject categorization "climate change".

Because data directly measuring concern is not available through GDELT, we rely on the assumption that shocks in climate change news (our variable *ClimateNewsCoverageChange)* translates to shocks to climate change concern among investors. To distinguish months of high and low climate change news coverage, we construct a dummy variable, $High_CNCC_{it}$, that takes the value of one when *ClimateNewsCoverageChange* is positive. The $High_CNCC_{it}$ captures months, in each country, with unexpected increases in climate change news that are not cyclical, seasonal or belonging to a past pattern.

Climate change news sentiment

As described in Section 3.1, the measure of climate change news coverage risks miscapturing positive news discussions. While the news may reflect increased public attention to climate change, it might not necessarily capture increased climate change concerns, limiting the use of ClimateNewsCoverageChange as a proxy of climate change concern shocks. With inspiration taken from the article by Engle, Giglio, Kelly, Lee, and Stroebel (2020), we address this risk by applying the sentiment analysis by GDELT on the climate change news articles.Other research also shows the effect of tone on how news affects trading behavior (Baker & Wurgler, 2006; Briere et al., 2023) We use the GDELT tone score, which is the daily average tone of articles with chosen keywords (same as for *CNCC*). We average the daily values for the tone score to the monthly level, then following Engle et al. (2020), we measure shocks in monthly tone score by constructing values of *ClimateNewsSentimentChange* for news articles published in country i in month t as residuals from a first-order autoregressive model, AR(1), depicted in Eq.(4). The autoregressive model relates the tone score, denoted Y, to its past values, with the residual representing the part of the current month's tone score not predicted by previous month's tone score. *ClimateNewsSentimentChange* therefore captures shocks in the average tone of news articles on climate change. The rationale for using shocks in tone score rather than the raw tone score is that shocks to raw sentiments have exerted significant impacts on stock returns (Shen et al., 2022). We then construct a dummy variable, Low_CNSC_{it} that takes the value of one when

$ClimateNewsSentimentChange_{it}$ is below the city's historical monthly median. *Low_CNSS* captures months, within each country, where climate change news articles have unexpectedly *low* tone scores. In these months, climate change has suddenly been portrayed mostly negatively in the news media. Following Ardia et al. (2022), we assume that negative sentiment in climate change news coverage is more indicative of public concern about climate change.

$$\text{AR(1): } Y_{it} = \beta_0 + \beta_1 Y_{it-1} + \epsilon_{it} \qquad \text{Eq.(4)}$$

Pollution news coverage and sentiment

We specifically look at air pollution news coverage and sentiment to understand its impact on our relationships of interest. The reason for narrowing to the term "air pollution" is twofold. First, the CCV of Engle et al. (2020) does not include the term "air pollution". Given this is our variable of interest, we are interested in addressing this highly relevant body of news that might be missing from climate change news. Second, Fisman, Ghosh, Sarkar, and Zhang (2023) find that when alerted about harmful air quality, retail investors reacted negatively towards "brown" stocks"[11], while institutional investors do not react (or slightly positively). Taken together, we believe that air pollution news is an important variable that can affect the relationship between air pollution and EMC returns.

We construct $PollutionNewsCoverageChange_{it}$ similar to $ClimateNewsCoverageChange_{it}$ defined as the log change in the total number of air pollution news articles published in country *i* in month *t*, adjusted for seasonality using Eq.(1), and the dummy variable, $High_PNCC_{it}$, which takes the value of one when $PollutionNewsCoverageChange_{it}$ is positive. *High_PNCC* is interpreted as months, within each country, with unexpected increases in air pollution news. $PollutionNewsSentimentChange_{it}$, similar to $ClimateNewsSentimentChange_{it}$, is defined as the shock in the average tone of news articles on air pollution and Low_PNSC_{it} is the dummy variable that equals one when $PollutionNewsSentimentChange_{it}$ falls below the city's historical monthly median. *Low_PNSC* captures months, within each country, with air pollution news articles that have unexpectedly low (negative) tone scores.

We construct climate change news coverage, air pollution news coverage variables using the same method as for the variable DSVI (log change). We believe this is an appropriate specification because all these variables are constructed using raw counts. On the other hand, sentiment variable data is already processed and therefore normalized, making it more appropriate for an AR(1) model. Using the AR(1) model on news coverage would mean taking residuals of raw numbers without the underlying variable being accounted for, which could lead to ignoring cyclical, seasonal or predictable variations.

[11] Fisman et al. (2023) define brown stocks and green stocks following the definition of Choi et al. (2020), which is replicated in this paper. In contrast, Fisman et al. (2023) look at stocks listed in NSE, an Indian stock exchange, whereas this paper examines European stock exchanges.

3.3 Data sample

We retrieve data for European exchange cities, and their corresponding countries, based on the list of exchanges categorized as "European" by DataStream. DataStream lists 48 exchange cities, and 38 countries, as belonging to Europe.[12]

Table 1: Summary statistics (with PM2.5)

Panel A: Initial sample

Variable	Obs	Mean	Std. Dev.	Min	Max	P10	P25	P50	P75	P90
Ab_AP (PM2.5)	3305	-2.971	5.066	-47.602	28.675	-8.473	-4.842	-2.531	-.568	1.795
DSVI(city)	5148	-.417	72.796	-352.182	371.149	-51.986	-21.146	-.08	19.596	54.138
DSVI(country)	4524	-.532	67.914	-453.732	423.668	-47.538	-20.004	-.284	18.517	46.34
Equal-Weighted EMC(adj)	4906	-.035	4.754	-50.811	95.393	-4.474	-1.803	0	1.722	4.361
Equal-Weighted EMC(raw)	4906	.009	7.543	-114.802	180.486	-5.999	-2.46	-.029	2.368	5.941
Equal-Weighted EMISSION	4911	-.024	3.763	-44.459	81.084	-3.339	-1.344	0	1.259	3.239
Equal-Weighted CLEAN	5143	.01	1.108	-14.309	12.262	-.958	-.367	0	.389	1
Equal-Weighted EMC(t+1,t+3)	4906	-.065	6.897	-48.876	45.607	-7.131	-3.076	0	3.064	7.123
Equal-Weighted EMC(t+1,t+6)	4906	-.199	9.934	-74.306	68.772	-10.688	-4.528	0	4.509	10.635
Equal-Weighted EMC(t+1,t+12)	4906	-.4	15.017	-91.11	91.745	-17.057	-7.055	0	7.12	15.809
Value-Weighted EMC(adj)	4906	-.039	5.766	-54.536	67.789	-6.028	-2.565	0	2.451	5.754
Value-Weighted EMC(raw)	4906	-.107	8.163	-201.598	103.01	-7.388	-3.393	-.236	3.04	7.122
Value-Weighted EMISSION	4911	-.06	4.111	-48.718	42.099	-4.222	-1.782	0	1.694	4.152
Value-Weighted CLEAN	5143	-.045	3.193	-55.042	25.287	-2.53	-.912	0	1.023	2.511
Value-Weighted EMC(t+1,t+3)	4906	-.141	9.457	-60.182	96.872	-10.045	-4.682	0	3.937	10.098
Value-Weighted EMC(t+1,t+6)	4906	-.297	13.927	-79.353	174.51	-15.058	-6.969	-.029	6.059	14.626
Value-Weighted EMC(t+1,t+12)	4906	-.602	20.873	-112.293	190.859	-23.224	-10.338	0	8.498	19.795
Ab_Temp	5141	.617	3.086	-12.225	14.169	-3.161	-1.351	.615	2.613	4.514
Reg_Score	2376	3.237	.748	.722	4.889	2.5	2.889	3.25	3.75	4.028
Climate News Coverage Change	3135	0	25.223	-207.089	104.45	-30.568	-15.761	-.229	15.872	30.587
Climate News Sentiment Change	3135	.016	.49	-4.827	4.1	-.56	-.271	.033	.304	.564
Pollution News Coverage Change	3135	0	29.639	-151.654	172.411	-37.322	-19.077	-.039	18.82	37.288
Pollution News Sentiment Change	3135	.006	.951	-4.503	6.061	-1.108	-.536	.011	.526	1.15

Panel B: Final sample (equal-weighted EMC returns)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
EMC(adj)	3061	-.001	4.589	-3.986	-1.651	0	1.505	3.859
EMC(raw)	3061	.05	8.355	-5.669	-2.297	-.005	2.153	5.39
EMISSION	3061	.002	3.721	-2.972	-1.221	0	1.103	2.931
CLEAN	3061	.002	1.037	-.896	-.348	0	.368	.932
EMC(t+1,t+3)	3061	.024	6.287	-6.162	-2.729	0	2.733	6.552
EMC(t+1,t+6)	3061	.003	9.058	-9.129	-4.013	0	3.926	9.791
EMC(t+1,t+12)	3061	-.025	13.512	-14.07	-6.173	0	6.34	14.12

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
DSVI(city)	3298	-.356	73.203	-50.429	-20.647	0	19.877	51.321
DSVI(country)	2962	-.576	68.497	-48.332	-20.647	-.08	19.324	46.428
Aver_AP	3298	15.877	6.002	8.363	11.69	15.805	19.382	23.456
Mon_AP	3298	.236	6.41	-7.206	-2.678	-.188	2.409	7.157
Ab_AP	3298	-2.974	5.07	-8.509	-4.844	-2.533	-.568	1.796
Ab_Temp	3298	.602	3.069	-3.203	-1.372	.606	2.604	4.479

Panel C: Final sample (value-weighted EMC returns)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
EMC(adj)	3061	-.11	5.083	-5.188	-2.239	0	2.126	5.091
EMC(raw)	3061	-.211	8.562	-6.682	-3.127	-.312	2.772	6.441
EMISSION	3061	-.094	3.891	-3.809	-1.606	0	1.492	3.643
CLEAN	3061	.015	2.501	-2.045	-.811	0	.968	2.232
Ab_Temp	3061	.583	3.043	-3.185	-1.38	.571	2.582	4.43

Note: The table presents the summary statistics for the independent and dependent variables employed in the main analyses. Panel A uses the initial sample, while Panel B and C use the main final sample. Ab_AP (PM2.5) denotes abnormal air pollution measured by PM2.5. DSVI denotes the monthly logarithmic change in Google SVI of the topic "global warming", measured at both city and country levels. Portfolio return, expressed in percentage term, is calculated as the average raw or size-adjusted return of stocks in month t, using equal or value weights. Size-adjusted return is computed as the raw return minus the average return of stocks in the same size quintile by each exchange. The portfolios EMISSION and CLEAN are constructed based on firms' industry subsector classifications, with high-carbon industries defined according to the IPCC classification. EMC equals EMISSION minus CLEAN. EMC(adj) is calculated using size-adjusted returns; EMC(raw) is calculated using raw returns. Ab_Temp denotes abnormal temperature. Climate News Coverage Change and Pollution News Coverage Change

[12] The list of all European exchange cities and countries is provided in Table 2A in the Appendix.

are the monthly log changes in the number of climate change and air pollution news articles, respectively. Climate News Sentiment Change and Pollution News Sentiment Change are the shocks in the monthly average tone of climate change and air pollution news articles, respectively.

The initial sample, shown in Panel A of Table 1, includes 4,911 high-emission stocks and 5,143 low-emission stocks, for which we have data on stock price, market capitalization, and industry subsector code; any stock with missing industry subsector code is dropped. After merging this initial sample with PM2.5 air pollution and Google SVI data, we dropped observations for city (or country) and date combinations for which either of these two were unavailable. As shown in the summary statistics in Panels B and C, this left us with a main final sample of 3,061 high-emission and 3,061 low-emission stocks, which covers 33 exchange cities and 29 countries in Europe. This sample construction leads to some loss of information. First, requiring industry subsector codes removes a small number of generally smaller or less-covered firms. Second, merging with PM2.5 and Google SVI data reduces geographic coverage from 48 to 33 exchange cities and from 38 to 29 countries. However, we believe that this choice mainly affects smaller markets and locations with limited environmental monitoring or incomplete search data, as the sample still includes the larger cities such as London and Frankfurt am Main. As a result, the final sample remains broad and diverse across Europe but is somewhat less representative of the smallest exchanges. Nonetheless, the restrictions improve internal consistency by ensuring that all included observations have pollution, search frequency, and financial data.

For the robustness test using MSCI ratings as an alternative method to classify high- and low-emission firms, we further merge the main sample with firm-level data on carbon emission score and ISIN number, and drop stocks with missing values. We end up with a sample containing 351 observations and covering only 5 exchange cities, which limits geographic representativeness relative to the full set of 48 European exchange locations, and the results should be interpreted with caution.[13] In later tests, we also merge the main sample with country-level environmental policy stringency score data resulting in a sample of 1,475 observations for 22 countries, as well as with climate change and air pollution news data, resulting in samples of 1,852 observations for 22 countries. These samples cover more than half of the European countries, but might be interpreted as more representative of countries with more established monitoring systems and reporting infrastructure.

In Table 4A in the Appendix, we outline the different samples used for regressions with PM10 abnormal pollution – the main sample contains 3,239 observations, covering 36 cities and 32 countries, meaning a slightly better geographical coverage than that based on PM2.5. However, the other samples, although covering the same number of cities or countries, have a lower number of observations.

The summary statistics indicate that the mean *DSVI* values are negative but near zero (–0.356% and –0.576%). In comparison, the mean values of *Aver_AP*, *Mon_AP*, *Ab_AP*, and *Ab_Temp* are 15.9, 0.2, –3.0 μg/m^3 of PM2.5, and 0.60ºF, respectively. Overall, the summary statistics of the city- and country-level DSVIs are similar. The summary statistics for PM10 (Table 4A) shows similar trends as those for PM2.5.

[13] The five cities include: Berlin, Frankfurt am Main, London, Vienna, and Zurich.

Table 2: Correlation matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Ab_AP (PM10)	1.00											
(2) Ab_AP (PM2.5)	0.65***	1.00										
(3) DSVI(city)	0.00	-0.01	1.00									
(4) DSVI(country)	0.00	0.02	0.70***	1.00								
(5) Equal-weighted EMC(adj)	0.02	0.01	-0.02	-0.01	1.00							
(6) Value-weighted EMC(adj)	0.05**	0.03*	-0.01	-0.01	0.49***	1.00						
(7) Reg_Score	0.00	-0.02	0.00	0.01	0.01	-0.02	1.00					
(8) Ab_Temp	0.03*	-0.11***	0.03**	0.02	-0.01	0.00	0.07***	1.00				
(9) CNCC	0.01	0.00	0.07***	0.07***	-0.02	-0.01	0.01	0.11***	1.00			
(10) CNSC	0.00	0.01	-0.01	-0.01	0.03*	0.02	-0.11***	-0.05***	0.00	1.00		
(11) PNCC	0.06**	0.05**	-0.01	0.01	-0.03	0.01	0.00	0.00	0.26***	-0.07***	1.00	
(12) PNSC	0.06**	0.05**	0.03	0.03	0.04**	0.01	-0.11***	-0.06***	-0.02	0.29***	-0.11***	1.00

Note: The table reports the correlation matrix. CNCC, CNSC, PNCC, and PNSC denote Climate News Coverage Change, Climate News Sentiment Change, Pollution News Coverage Change, and Pollution News Sentiment Change, respectively. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

In Table 2, we observe the correlation matrix between, for instance, *Ab_AP* (PM2.5 and PM10), *DSVI(city)*, *DSVI(country)*, equal- and value-weighted *EMC* size-adjusted returns, and *Ab_Temp*. We observe that *DSVI(city)* and *DSVI(country)* are strongly positively correlated at the 1% significance level. Abnormal air pollution is not significantly correlated with equal-weighted *EMC* return but shows significant positive, though weak, correlation with value-weighted *EMC* return. The different climate change concern measures are, overall, significantly correlated with each other.

4. Empirical results

4.1 Effect of air pollution on investor attention

We start with testing whether people's attention to climate change varies with abnormal local air pollution. Following Choi et al. (2020), we run the following regression:

$$DSVI_{it} = \alpha + \beta_1 Ab_AP_{it} + \beta_2 Ab_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it} \qquad \text{Eq.(5)}$$

where $YearMonth_t$ is the year-month fixed effects (FE), included to observe the relationship from geographical variation (Choi et al., 2020). In this regression, and all following regressions, standard errors are clustered by exchange city to account for heteroscedasticity across clusters of observations (Abadie, Athey, Imbens, Wooldrige, 2022).[14] Abnormal local temperature, *Ab_Temp*, is included as a control variable. The coefficient of interest is β_1, which captures the effect of abnormal local air pollution, specifically PM2.5, on people's attention to climate change, measured by the city's monthly change in Google *SVI* of the topic "global warming".

[14] We deviate from Choi et al. (2020) by clustering only by exchange city instead of both exchange city and year-month. Our regressions have one observation for each city-year-month, and clustering by both leaves no variation, making the two-way clustering redundant.

Table 3: Regression of DSVI on abnormal air pollution (PM2.5)

	(1) DSVI(city)	(2) DSVI(city)	(3) DSVI(country)	(4) DSVI(country)
Ab_AP	-0.225		0.001	
	(-1.33)		(0.01)	
Ab_AP Q2		-6.163		0.973
		(-1.56)		(0.22)
Ab_AP Q3		-7.723*		-3.341
		(-1.99)		(-1.01)
Ab_AP Q4		-2.549		1.520
		(-0.61)		(0.42)
Ab_AP Q5		-7.026**		-1.150
		(-2.26)		(-0.44)
Ab_Temp	0.069	0.035	0.019	0.027
	(0.11)	(0.05)	(0.03)	(0.04)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	3,298	3,298	2,962	2,962
Adj. R^2	0.070	0.070	0.097	0.097

Note: The table presents results from regressions of city-level (Columns 1 and 2) and country-level (Columns 3 and 4) monthly log changes in Google SVI of the topic global warming (DSVI) on city-level abnormal air pollution (Ab_AP), measured by PM2.5. Ab_AP Q2 to Ab_AP Q5 denote quintile dummy variables. Abnormal temperature (Ab_Temp) is a control variable. The sample runs from January 2012 to December 2024, including 33 exchange cities. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 3 presents the results of estimating Eq.(5). In Column 1, the coefficient estimate of *Ab_AP* is statistically insignificant, which does not support the hypothesis that people increase climate change attention when experiencing abnormally high air pollution. In Column 2, we allow Ab_AP_{it} to have a non-linear effect on $DSVI_{it}$ by sorting months into quintiles based on Ab_AP_{it} in city *i*, and re-estimating Eq.(5) using quintile dummies Ab_AP_{it} *Q1–5* that correspond to one if a month belongs to quintiles 1–5, respectively. The omitted category is Ab_AP_{it} *Q1*, which captures the least polluted months, and Ab_AP_{it} *Q5* captures the most polluted months. The results indicate that the effect of abnormal PM2.5 on the Google *SVI* for topic "global warming" becomes significant only during months with relatively high pollution levels. The negative coefficient estimates of the third and fifth quintile dummies are significant at 10% and 5% respectively, suggesting that, when abnormal PM2.5 grows from the smallest 20% to median or the largest 20%, people search 7–7.7% less about global warming. This indicates that *DSVI* changes with pollution levels, although inconsistently. Relative to the least polluted months, the most polluted months are associated with lower *DSVI* with greater statistical certainty (at 5% significance level), while median polluted months show greater magnitude but weaker statistical certainty (at 10% significance level).

Table 4: Regression of DSVI on abnormal air pollution (PM10)

	(1) DSVI(city)	(2) DSVI(city)	(3) DSVI(country)	(4) DSVI(country)
Ab_AP	-0.053		0.085	
	(-0.40)		(0.58)	
Ab_AP Q2		-2.568		-3.457
		(-0.51)		(-1.12)
Ab_AP Q3		-3.442		-7.216*
		(-1.00)		(-1.97)
Ab_AP Q4		-3.163		1.022
		(-0.87)		(0.18)
Ab_AP Q5		-3.065		-2.496
		(-1.07)		(-0.70)
Ab_Temp	0.178	0.185	-0.101	-0.129
	(0.25)	(0.26)	(-0.15)	(-0.19)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	3,483	3,483	3,147	3,147
Adj. R^2	0.065	0.064	0.072	0.073

Note: The table reports regression results of monthly log changes in Google SVI of "global warming" (DSVI) on abnormal air pollution (PM10). The sample ranges from January 2012 to December 2024, with 36 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

To investigate further, we replicate our analysis on abnormal PM10 (Table 4). The results are insignificant. Finally, we repeat the regressions for PM2.5 and PM10 by replacing the city-level *DSVI* with the country-level *DSVI* (Table 3 and 4, Columns 3 and 4). We see no significant results for PM2.5. For PM10, *DSVI* is 7.2% lower in a Q3 month compared to a Q1 month at the 10% level. It is important to note that the coefficient estimate for Q3 PM2.5 at the city level is extremely similar to Q3 PM10 at the country level. We find significant results at Q3 for both pollutants, while we see inconsistencies between city and country levels. This implies median and largest pollution shocks do not systematically drive searches towards climate change.

4.2 Effect of air pollution on portfolio return

Next, we examine how abnormal local pollution affects the stock returns of high- and low-emission firms differently. In line with Choi et al. (2020), we run the following regression:

$$EMC_{it} = \alpha + \beta_1 Ab_AP_{it} + \beta_2 Ab_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it} \qquad \text{Eq.(6)}$$

where EMC_{it} is the equal-weighted or value-weighted, raw or size-adjusted return of the *EMC* portfolio in city *i* in month *t*. The regression controls for abnormal temperature, Ab_Temp_{it}, and includes year-month FE. The coefficient of interest is β_1, which measures the percentage change in the monthly *EMC* portfolio return caused by a one-unit change in *Ab_AP* PM2.5. The regression results are represented in Panel A (equal-weighted returns) and B (value-weighted returns).

Table 5: Emission-minus-clean portfolio return and abnormal air pollution (PM2.5)

Panel A: Equal-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.017		0.017			
	(0.91)		(0.66)			
Ab_AP Q2		0.329		-0.756	0.312	-0.018
		(0.83)		(-0.74)	(0.93)	(-0.26)
Ab_AP Q3		0.147		-0.600	0.171	0.024
		(0.61)		(-0.98)	(0.82)	(0.52)
Ab_AP Q4		0.184		-0.665	0.174	-0.010
		(0.85)		(-0.93)	(0.98)	(-0.21)
Ab_AP Q5		0.170		-0.252	0.188	0.017
		(0.46)		(-0.38)	(0.62)	(0.22)
Ab_Temp	0.059**	0.060*	0.002	-0.011	0.048*	-0.012*
	(2.06)	(2.02)	(0.05)	(-0.25)	(1.99)	(-1.77)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,061	3,061	3,061	3,061	3,061	3,061
Adj. R^2	0.011	0.010	0.004	0.004	0.008	0.014

Panel B: Value-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.037		0.038			
	(1.59)		(1.68)			
Ab_AP Q2		0.015		-1.091	0.213	0.199
		(0.04)		(-1.26)	(0.71)	(1.32)
Ab_AP Q3		0.363		-0.371	0.323	-0.040
		(1.18)		(-0.75)	(1.43)	(-0.27)
Ab_AP Q4		0.273		-0.378	0.389	0.116
		(0.83)		(-0.68)	(1.56)	(0.71)
Ab_AP Q5		0.363		-0.008	0.317	-0.046
		(0.76)		(-0.01)	(0.87)	(-0.23)
Ab_Temp	0.043	0.038	0.002	-0.018	0.041	0.003
	(1.12)	(0.94)	(0.03)	(-0.32)	(1.37)	(0.17)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,061	3,061	3,061	3,061	3,061	3,061
Adj. R^2	0.008	0.007	0.007	0.007	0.002	0.007

Note: The table reports results from regressions of emission-minus-clean (EMC) portfolio returns on contemporaneous abnormal air pollution (PM2.5) variables, controlling for abnormal temperature (Ab_Temp). Portfolio return is expressed as a percentage. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. The sample ranges from January 2012 to December 2024, with 33 exchange cities. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 5 Panel A Column 1 provides no empirical evidence of abnormal PM2.5 affecting *EMC* size-adjusted returns. Column 2 replaces Ab_AP_{it} with the quintile dummies Ab_AP_{it} *Q1–5* based on a city's monthly PM2.5 shocks. Although *DSVI* was found to be lower in the most polluted months compared to the least polluted months in Section 4.1, monthly *EMC* size-adjusted returns do not significantly vary with abnormal PM2.5. Similar results are found for raw returns in Columns 3 and 4. Columns 5 and 6 report results for *EMISSION* and *CLEAN* portfolio size-adjusted returns. Neither *EMISSION* nor *CLEAN* portfolio size-adjusted returns change with PM2.5 quintile dummies, suggesting no significant effect of local PM2.5 shocks on size-adjusted returns. Overall, Table 5 provides no empirical evidence that abnormal local PM2.5 explains *EMC* returns.

Table 6: Emission-minus-clean portfolio return and abnormal air pollution (PM10)

Panel A: Equal-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.039*		0.010			
	(1.87)		(0.55)			
Ab_AP Q2		-0.103		-0.861	-0.018	0.085
		(-0.36)		(-1.25)	(-0.08)	(0.86)
Ab_AP Q3		0.092		0.119	0.193	0.100
		(0.27)		(0.16)	(0.91)	(0.57)
Ab_AP Q4		-0.069		-0.683	-0.038	0.031
		(-0.29)		(-1.06)	(-0.20)	(0.56)
Ab_AP Q5		0.239		-0.551	0.032	-0.207
		(0.69)		(-0.87)	(0.14)	(-1.26)
Ab_Temp	0.052	0.054	0.036	0.041	0.044*	-0.009
	(1.59)	(1.57)	(0.77)	(0.88)	(1.72)	(-0.93)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,239	3,239	3,239	3,239	3,239	3,239
Adj. R^2	0.004	0.001	-0.002	-0.002	0.005	-0.001

Panel B: Value-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.028		0.027			
	(1.63)		(1.28)			
Ab_AP Q2		0.485		-0.115	0.321	-0.164
		(1.54)		(-0.18)	(1.55)	(-0.78)
Ab_AP Q3		0.607		0.780	0.545**	-0.061
		(1.61)		(1.37)	(2.11)	(-0.31)
Ab_AP Q4		0.432		0.160	0.436	0.004
		(1.12)		(0.31)	(1.33)	(0.02)
Ab_AP Q5		0.678**		0.688	0.568**	-0.110
		(2.09)		(1.34)	(2.36)	(-0.64)
Ab_Temp	0.057	0.057	0.032	0.027	0.040	-0.017
	(1.26)	(1.22)	(0.61)	(0.50)	(1.15)	(-0.97)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,239	3,239	3,239	3,239	3,239	3,239
Adj. R^2	0.006	0.005	0.005	0.005	0.007	0.004

Note: The table reports results from regressions of emission-minus-clean (EMC) portfolio returns on contemporaneous abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). Portfolio return is expressed as a percentage. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. The sample ranges from January 2012 to December 2024, with 36 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Next, we estimate Eq.(6) for PM10 (Table 6). At the 10% significance level, the monthly equal-weighted *EMC* size-adjusted return increases by 3.9bps with each μg/m3 (microgram) of abnormal PM10 (Panel A Column 1). We cannot identify differential effects across pollution quintiles (Column 2). In Panel B, weighing for value, we see Q5 months driving 68bps higher EMC size-adjusted returns than Q1 months (Column 2), suggesting that the effect is likely driven primarily by larger market cap stocks that receive a larger weight in Panel B. The 68bps higher return in Q5 months than Q1 months is driven by *EMISSION* size-adjusted stocks (Panel B Column 5) earning a similarly positive return at 5% significance level. We also see that *EMISSION* size-adjusted stocks earn 55bps higher returns in Q3 months compared to months with the lowest abnormal air pollution. Overall, relative to months with the lowest pollution shocks, we see months with largest pollution shocks driving 68bps higher return in *EMC*, as well as months with median pollution shocks driving 55bps higher returns in *EMISSION* stocks.

In general, we find that abnormal PM2.5 does not affect *EMC* returns. We also find that months with highest abnormal PM10 drive higher *EMC* returns for larger cap stocks, primarily driven by higher returns of *EMISSION* stocks. We note that in Table 4, a month with median relative to low abnormal PM10 was associated with a 7% lower attention (DSVI) to global warming. Taking the country-level specifications of PM10-DSVI and PM10-EMC (value weighted) together, we see that months with median abnormal PM10 show relatively lower attention towards global warming and generate relatively higher returns for high-emission stocks, especially larger cap stocks.

Long-term portfolio return

Similar to Choi et al. (2020), we examine the long-term performance of the *EMC* portfolio subsequent to a month with abnormal PM2.5:

$$EMC_{i,t+1,t+n} = \alpha + \beta_1 Ab_AP_{it} + \beta_2 Ab_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it} \quad \text{Eq.(7)}$$

where n = {3,6,12} and the return of the *EMC* portfolio in city i is measured from month $t+1$ to month $t+n$. Ab_Temp_{it} is controlled for and year-month fixed effects are included. The coefficient of interest is β_1, which estimates the effect of abnormal local air pollution on long-term *EMC* portfolio returns. A negative or zero β_1 suggests that even though investors are not reacting to abnormal PM2.5 in the short run (Table 5), they might recognize the negative impact of air pollution on the climate and avoid highly climate-sensitive stocks in the long run. We test whether investors react to the risk of climate change following abnormal PM2.5 exposure in 3 to 12 months after the shock. This would mean that, although abnormal PM2.5 exposure has no short-run impact on *EMC* return, investors update beliefs about and sell high-emission stocks slowly. On the other hand, a positive β_1 suggests that investors underreact in a given month t with abnormal PM2.5 exposure, thus foregoing returns and gains from holding high-emission stocks in the long run. Table 7 presents the results.

Table 7: Long-term EMC returns subsequent to abnormal pollution (PM2.5)

Panel A: Equal-weighted EMC returns

	(1) EMC(adj, t+1,t+3)	(2) EMC(adj, t+1,t+3)	(3) EMC(adj, t+1,t+6)	(4) EMC(adj, t+1,t+6)	(5) EMC(adj, t+1,t+12)	(6) EMC(adj, t+1,t+12)
Ab_AP	0.059		0.046		0.058	
	(1.16)		(0.48)		(0.43)	
Ab_AP Q2		-0.136		0.366		0.319
		(-0.39)		(0.39)		(0.31)
Ab_AP Q3		0.294		0.556		0.528
		(0.61)		(0.70)		(0.49)
Ab_AP Q4		0.332		0.636		0.126
		(0.49)		(0.63)		(0.10)
Ab_AP Q5		0.739		1.107		1.310
		(1.18)		(0.82)		(0.62)
Ab_Temp	0.050	0.038	0.028	0.023	0.194	0.186
	(1.23)	(0.95)	(0.26)	(0.22)	(0.96)	(0.94)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,061	3,061	3,061	3,061	3,061	3,061
Adj. R^2	0.018	0.017	0.014	0.014	0.036	0.036

Panel B: Value-weighted EMC returns

	(1) EMC(adj, t+1,t+3)	(2) EMC(adj, t+1,t+3)	(3) EMC(adj, t+1,t+6)	(4) EMC(adj, t+1,t+6)	(5) EMC(adj, t+1,t+12)	(6) EMC(adj, t+1,t+12)
Ab_AP	0.075		0.100		0.146	
	(1.27)		(1.08)		(1.15)	
Ab_AP Q2		0.514		0.043		-0.347
		(0.84)		(0.04)		(-0.25)
Ab_AP Q3		0.772		0.902		0.403
		(1.08)		(0.79)		(0.27)
Ab_AP Q4		0.633		0.838		-0.120
		(0.88)		(0.81)		(-0.09)
Ab_AP Q5		0.344		0.331		0.168
		(0.47)		(0.24)		(0.07)
Ab_Temp	-0.032	-0.035	-0.124	-0.136	0.015	-0.010
	(-0.42)	(-0.45)	(-0.68)	(-0.75)	(0.05)	(-0.04)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,061	3,061	3,061	3,061	3,061	3,061
Adj. R^2	0.013	0.011	0.009	0.007	0.005	0.002

Note: The table presents regression results of EMC(t+1, t+3), EMC(t+1, t+6), and EMC(t+1,t+12) on abnormal air pollution (PM2.5) at month t and controls for abnormal temperature (Ab_Temp). EMC(t+1, t+3), EMC(t+1, t+6) are calculated as the equal-weighted or value-weighted average of size-adjusted stock returns over months t+1 to t+3, t+1 to t+6, and t+1 to t+12.. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. The sample ranges from January 2012 to December 2024, with 33 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

The coefficient estimates of *Ab_AP* (Columns 1, 3, and 5 of Table 7), as well as the coefficient estimates of PM2.5 quintiles (Columns 2, 4, and 6), are statistically insignificant. These results indicate that the effect of abnormal PM2.5 on the *EMC*

portfolio (and its components *EMISSION* and *CLEAN*) remains statistically insignificant in the 3 to 12 months after month *t*, showing neither signs of slow belief updating among investors or return reversal. We observe no effect of local abnormal PM2.5 exposure on *EMC* portfolio return in the short nor the long run. In Table 6A (Appendix), we repeat the regression in Eq.(7) using PM10 as the air pollution measure. We find similar results indicating that abnormal PM10 has no effect on the *EMC* portfolio or its components in 3 to 12 months after month *t*.

4.3 Robustness tests

Industry effects

In the previous tests, firms were classified as high- or low-emission based on the IPCC industry classification, not the firm-level carbon emissions. A potential limitation of the IPCC industry classification is that it may capture industry effects. We address this concern by implementing two complementary robustness tests. The first test reclassifies firms as high- and low-emission based on their MSCI carbon emission scores. This test accounts for industry differences, because the carbon emission scores are industry-adjusted, enabling comparisons of high- and low-emission firms within the same industry. Using this alternative firm classification, we rerun the regression in Eq.(6) using equal-weighted (Table 8 Columns 1 and 2) and value-weighted (Columns 3 and 4) *EMC* size-adjusted returns.

Table 8: EMC portfolio return, abnormal air pollution (PM2.5), MSCI

	Equal-weighted EMC(adj)		Value-weighted EMC(adj)	
	(1)	(2)	(3)	(4)
Ab_AP	0.051		0.046	
	(0.91)		(0.28)	
Ab_AP Q2		-0.377		0.969
		(-0.70)		(0.93)
Ab_AP Q3		-0.480		1.501
		(-0.62)		(0.87)
Ab_AP Q4		-0.327		1.476
		(-0.30)		(0.94)
Ab_AP Q5		-0.674		-0.024
		(-1.04)		(-0.01)
Ab_Temp	0.422**	0.409**	-0.131	-0.108
	(3.54)	(3.36)	(-0.38)	(-0.32)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	351	351	343	343
Adj. R^2	0.271	0.262	0.148	0.144

Note: The table presents results from regressions of EMC size-adjusted returns on abnormal air pollution (PM2.5) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN, with EMISSION including stocks with MSCI carbon emission scores lower than 3 and CLEAN including stocks with scores higher than 7. Portfolio returns, expressed as percentages, are equal-weighted (Columns 1 and 2) and value-weighted (Columns 3 and 4). The sample ranges from January 2012 to December 2022, with 5 exchange cities. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

The results are consistent with those reported in the previous tables; *EMC* returns do not significantly vary with a city's abnormal PM2.5 exposure. Reported in the Appendix, Table 7A using PM10 further confirms this pattern, showing that, after accounting for industry differences, *EMC* returns are not related to abnormal PM10 exposure. Reconciling this finding with the results in Table 6, we hypothesize that the higher

returns of the *EMC* size-adjusted portfolio and *EMISSION* during months with the highest and median levels of abnormal PM10 can be attributed to industry effects. However, since the MSCI carbon emission score is only available for a limited number of exchanges and firms, the test is conducted with a smaller sample (only 5 exchange cities), implying reduced statistical power and external validity.

Moreover, returns of certain high-emission industries may be influenced by oil price fluctuations. Given we find positive *EMC* returns for abnormal PM10, we further examine the risk of potential industry effects in Table 9. Following Choi et al. (2020), we conduct separate analyses for energy firms (belonging to the IPCC Energy sector) and other high-emission firms (falling within the remaining high-emission IPCC sectors). With the *EMISSION* portfolio being divided by Energy and Non-energy firms, we calculate the size-adjusted *EMC* portfolio returns, using equal weights (Panel A) and using value weights (Panel B), for each group. We re-estimate Eq.(6) for PM10, the sample including Energy firms in Columns 1 and 2 and for the sample excluding Energy firms in Columns 2 and 3.

Table 9: EMC portfolio return, abnormal air pollution (PM10), Energy vs. Non-energy

Panel A: Equal-weighted EMC returns

	Energy		Non-energy	
	(1)	(2)	(3)	(4)
Ab_AP	0.076		0.042*	
	(1.14)		(1.96)	
Ab_AP Q2		-0.119		-0.162
		(-0.12)		(-0.47)
Ab_AP Q3		0.873		0.013
		(1.50)		(0.04)
Ab_AP Q4		0.213		-0.213
		(0.27)		(-0.76)
Ab_AP Q5		0.856		0.207
		(0.71)		(0.48)
Ab_Temp	0.029	0.043	0.032	0.037
	(0.27)	(0.39)	(0.81)	(0.86)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,459	1,459	2,971	2,971
Adj. R^2	0.066	0.063	0.006	0.003

Panel B: Value-weighted EMC returns

	Energy		Non-energy	
	(1)	(2)	(3)	(4)
Ab_AP	0.035		0.031*	
	(0.68)		(1.85)	
Ab_AP Q2		0.135		0.506
		(0.12)		(1.52)
Ab_AP Q3		0.176		0.645
		(0.30)		(1.64)
Ab_AP Q4		-0.278		0.310
		(-0.36)		(0.70)
Ab_AP Q5		0.165		0.736*
		(0.16)		(1.92)
Ab_Temp	0.121	0.133	0.017	0.017
	(1.29)	(1.35)	(0.29)	(0.28)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,459	1,459	2,971	2,971
Adj. R^2	0.058	0.056	0.009	0.009

Note: The table shows results from regressions of EMC size-adjusted returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN. The EMISSION portfolio is divided by Energy and Non-energy firms, and EMC portfolio returns are calculated for each group. Panel A presents equal-weighted portfolio returns and Panel B presents value-weighted returns. The sample ranges from January 2012 to December 2024, with 36 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

The results in Table 9 indicate that only firms in the non-energy sample (high-emission firms not in the energy sector) experience a significant positive return of 3-4bps due to abnormal PM10 exposure. Similar to the results in Table 6, value-weighted *EMC* size-adjusted returns are relatively higher at the 10% significance level during months with highest abnormal PM10 exposure. Moving from a PM10 Q1 (least polluted) month to a Q5 (most polluted) month corresponds to a 74bps higher *EMC* size-adjusted return (value weighted). Reconciling with the previous results, this may suggest that larger cap non-energy, high-emission firms see relatively higher size-adjusted returns during the most and median polluted months. Compared to a higher return of 57bps in Q5 in *EMISSION* stocks (Table 6 Column 5), a higher return of 75bps in Q5 in non-energy emission stocks (Table 9) (a subset of *EMISSION* stocks in Table 6 Column 5) implies that the energy sector was dampening *EMC* value-weighted size-adjusted returns in Table 6. In Appendix Table 8A, we repeat the test for PM2.5, and find no significant results, in line with previous findings that PM2.5 does not affect *EMC* returns.

Monte Carlo Permutation Test

In an ideal scenario, we would like to conduct a placebo test similar to that of Choi et al. (2020) to examine whether the relationships (or lack thereof) between abnormal pollution exposure, attention to global warming, and EMC returns existed prior to 2012. However, we only have access to pollution data starting 2012, meaning a time-based placebo test is not feasible. We would expect to see weaker relationships between the three variables, as awareness and attention to pollution and global warming was significantly lower before, especially before the 2000s (Choi et al., 2020). As a replacement, we conduct Monte-Carlo Permutation Tests (MCPT) on our key variables. MPCT randomly shuffles (permutes) several times (we run 100 repetitions) our datasets to break any underlying pairwise relationships between pollution-attention and pollution-returns, generating a random distribution of the coefficients. This acts as a new baseline significance level, benchmarking the regression's coefficient to the newfound distribution of coefficients. This helps answer the question whether the coefficient found is by chance. For brevity, the test results are included in the Appendix. Charts 1–2 are robustness checks for Table 3–4. Charts 3–6 are robustness checks for Table 5–6. We compare the two-sided *p*-value from the MCPT with the significance levels of the corresponding regression tests and find that the MCPT results are in line with the findings. Specifically, abnormal PM2.5 or PM10 levels (as opposed to PM2.5 and PM10 quintiles) have no relationship with DSVI (Charts 1 and 2 have two-sided p-values larger than 10%). Chart 4's result supports that abnormal PM10 exposure drives positive significant *EMC* equal-weighted size-adjusted returns (Table 6 Panel A). Similarly, Charts 3, 5 and 6 support that abnormal PM10 exposure does not drive *EMC* value-weighted size-adjusted returns, and abnormal PM2.5 exposure does not drive *EMC* equal- and value-weighted size-adjusted returns.

4.4 Tests of potential mechanisms

Existing research outlines multiple mechanisms through which air pollution and other environmental conditions may influence stock market outcomes. Our baseline results in the previous section show no significant effect of abnormal PM2.5 exposure on stock return, and a significant positive effect of abnormal PM10 exposure that is likely due to non-energy high-emission firms. However, these tests may not fully capture the influence of such mechanisms. To address this, we conduct additional tests designed to evaluate specific channels that could generate effects otherwise undetected in our primary specifications. By exploring different channels in the air pollution-stock return relationship, we aim to improve our understanding of the underlying mechanisms through which air pollution may affect the stock market.

Firm performance

First, through its impact on firm performance, air pollution may affect investors' valuation of firms and thus their behavior toward trading the stocks of these firms. There are different ways through which local air pollution may affect firm performance. One channel is that air pollution may reduce firm performance by causing acute health problems and therefore reducing work productivity (Fu, Viard, Zhang, 2021). In addition, skilled workers who tend to have a greater demand for quality of life may have a greater knowledge and understanding of the harmful effects of air pollution (Arntz,

2010), and firms located in more polluted areas, as a result, become less capable of recruiting and retaining high-quality individuals, leading to a loss of human capital (Xue, Zhang, and Zhao, 2021). Xue et al. (2021) document more pronounced effects of air pollution on firm performance in industries highly dependent on human capital, including "innovative" industries where talent is essential. In particular, the firm performance of the following industries are harmed by air pollution: Biotechnology, Telecommunication, Computers, and Electronics, following the definition adopted by Ouimet and Zarutskie (2014). Using the SIC codes of these harmed, "innovative" industries provided by Ouimet and Zarutskie (2014), we hand-match their corresponding industry names with IPCC subsector names, and find that three of these four industries have industry subsectors classified as high-emission according to our IPCC classifications.[15]

Table 10: EMC portfolio return, abnormal air pollution (PM2.5), Harmed vs. Non-harmed

Panel A: Equal-weighted EMC returns

	Harmed		Non-harmed	
	(1)	(2)	(3)	(4)
Ab_AP	0.018		0.004	
	(1.22)		(0.15)	
Ab_AP Q2		-0.583		0.433
		(-1.38)		(0.95)
Ab_AP Q3		0.082		0.265
		(0.20)		(1.02)
Ab_AP Q4		-0.045		0.314
		(-0.09)		(1.21)
Ab_AP Q5		-0.060		0.125
		(-0.15)		(0.25)
Ab_Temp	-0.023	-0.029	0.056*	0.061*
	(-0.30)	(-0.38)	(1.74)	(1.86)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,967	1,967	2,780	2,780
Adj. R^2	-0.004	-0.004	0.008	0.008

Panel B: Value-weighted EMC returns

	Harmed		Non-harmed	
	(1)	(2)	(3)	(4)
Ab_AP	0.015		0.025	
	(0.38)		(0.76)	
Ab_AP Q2		-1.311**		0.166
		(-2.27)		(0.48)
Ab_AP Q3		-0.129		0.511
		(-0.36)		(1.49)
Ab_AP Q4		-0.523		0.354
		(-0.97)		(0.92)
Ab_AP Q5		-0.282		0.199
		(-0.42)		(0.34)
Ab_Temp	-0.052	-0.067	0.030	0.030
	(-0.64)	(-0.79)	(0.74)	(0.76)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,967	1,967	2,780	2,780
Adj. R^2	0.025	0.027	-0.005	-0.005

Note: The table shows results from regressions of EMC size-adjusted returns on abnormal air pollution (PM2.5) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN. EMISSION and CLEAN portfolios are formed based on firms' industry subsector codes. In Columns 1 and 2, EMISSION includes stocks belonging to industries defined as high-emission by IPCC and innovative by Ouimet and Zarutskie (2014). In Columns 3 and 4, EMISSION includes stocks belonging to the remaining high-emission industries as defined by IPCC. The sample ranges from January 2012 to December 2024, with 33 cities. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

In Table 10, we show the results for PM2.5 from dividing the *EMISSION* portfolio into "harmed" and "non-harmed" firms. In Columns 1 and 2, the *EMISSION* portfolio is formed using only firms in harmed industries. In Columns 3 and 4, the *EMISSION* portfolio includes firms belonging to the remaining non-harmed industries defined as high-emission by IPCC. The *CLEAN* portfolio stays unchanged. We calculate the size-adjusted EMC portfolio returns, using equal weights (Panel A) and value weights (Panel B), for each group and re-estimate Eq.(6) for abnormal PM2.5 exposure. Given the findings of Xue et al. (2021), while harmed firms may suffer from negative firm performance due to their high dependence on human capital, the non-harmed firms are unlikely to be affected by abnormal air pollution. We observe no significant relationship between abnormal PM2.5 exposure and *EMC* size-adjusted returns for the equal-weighted portfolio. For the value-weighted portfolio we obtain statistically significant negative results for harmed industries, which experience 1.3% lower return during months with Q2 abnormal PM2.5 exposure compared to Q1 months. This is

[15] We use https://www.sec.gov/search-filings/standard-industrial-classification-sic-code-list to find SIC code industry names, which we then hand-match to IPCC subsector names.

evidence that harmed high-emission firms suffer from lower stock returns through abnormal PM2.5 exposure in Q2 months than Q1 months compared to non-harmed high-emission firms. We note this is primarily driven by larger cap firms. This finding does not necessarily contradict the results in Table 6 (abnormal PM2.5 exposure does not affect EMC returns). In fact, it supports the idea that despite lower returns of innovative high-emission firms during months with certain exposure levels relative to months with the lowest exposure, conventional *EMC* portfolio returns are not affected by abnormal PM2.5 exposure, likely because harmed firms constitute 20% of all high-emission firms and under 6% of all firms by count.

Table 11: EMC portfolio return, abnormal air pollution (PM10), Harmed vs. Non-harmed

Panel A: Equal-weighted EMC returns

	Harmed		Non-harmed	
	(1)	(2)	(3)	(4)
Ab_AP	0.046		0.042**	
	(1.29)		(2.14)	
Ab_AP Q2		0.024		-0.163
		(0.05)		(-0.49)
Ab_AP Q3		0.246		-0.028
		(0.50)		(-0.08)
Ab_AP Q4		-0.528		-0.082
		(-1.04)		(-0.33)
Ab_AP Q5		0.185		0.246
		(0.26)		(0.66)
Ab_Temp	-0.010	0.002	0.015	0.019
	(-0.11)	(0.03)	(0.39)	(0.45)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,983	1,983	2,941	2,941
Adj. R^2	0.001	-0.001	0.004	0.001

Panel B: Value-weighted EMC returns

	Harmed		Non-harmed	
	(1)	(2)	(3)	(4)
Ab_AP	0.018		0.040***	
	(0.49)		(3.01)	
Ab_AP Q2		0.362		0.723**
		(0.81)		(2.11)
Ab_AP Q3		0.302		0.744*
		(0.74)		(1.95)
Ab_AP Q4		-0.884		0.563
		(-1.70)		(1.25)
Ab_AP Q5		0.332		0.793**
		(0.53)		(2.33)
Ab_Temp	0.009	0.016	0.012	0.016
	(0.10)	(0.19)	(0.22)	(0.26)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,983	1,983	2,941	2,941
Adj. R^2	0.025	0.027	0.001	-0.001

Note: The table shows results from regressions of EMC size-adjusted returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN. EMISSION and CLEAN portfolios are formed based on firms' industry subsector codes. The sample ranges from January 2012 to December 2024, with 36 exchange cities. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

For PM10, we observe a significant positive relationship between abnormal PM10 exposure and *EMC* size-adjusted returns for non-harmed high-emission stocks while harmed high-emission stocks remain unaffected (Table 11). While non-harmed firms observing positive returns is not necessarily in line with Xue et al. (2021), it aligns directionally in that non-harmed firms fare better than harmed firms during pollution exposure. It also aligns with previous findings of *EMC* portfolios earning positive returns in response to abnormal PM10 exposure. The *CLEAN* stocks are the same for both harmed and non-harmed portfolios, therefore it may be the high-emission stocks in the non-harmed portfolio driving additional returns. The finding persists in value-weighted portfolios (Panel B) with a similar economic magnitude of 4bps. In addition, we see that larger cap stocks are driving the additional return across abnormal exposure quintiles (compared to Q1) except Q4. This is in line with our results in Table 6, which sees around 68bps higher returns in Q5 months than Q1 months. However, this informs that not all high-emission firms are driving positive EMC returns in Table 6, and investors are more likely to buy non-harmed emission firms than harmed emission firms during abnormal PM10 exposure (as evidenced by *Ab_AP* being significant at the 1% level, which is greater than the significance of results in Table 3).

Taken together, these findings suggest that results in Table 6 are largely driven by positive investor response towards non-harmed high-emission industries during abnormal PM10 exposure, given that non-harmed stocks constitute around 80% of the *EMISSION* stocks by count. This is evidence that *EMISSION* stocks outperform *CLEAN*

stocks with increased abnormal PM10 exposure, the channel being that non-innovative high-emission firms outperform innovative ones.

Environmental policy stringency

We next explore channels that might affect the pollution-return relationship in the absence of any real change in firms' value; investors may still update their private beliefs about firms' value as they become more aware of climate risk. Because such beliefs are not directly observable, we study cases in which climate change is likely to adversely affect the future cash flows of high-emission firms. If investors revise their expectations about these firms' future cashflows, such revisions would be more prominent under these situations, leading to a possible observation of a negative link between high-emission firms' returns and local abnormal air pollution. Similar to Choi et al. (2020), we consider the impact of country-level environmental regulations on the relationship between pollution and returns. Stricter regulations can make it more expensive to emit carbon and other pollutants, or expose firms to more legislation or scrutiny. To test whether abnormal pollution has a differential effect on stock returns in countries with environmental regulatory systems of varying strengths, we re-estimate Eq.(6) for different *EMC* return variables, interacting abnormal pollution (PM2.5), *Ab_AP*, with a dummy variable for environmental policy stringency, denoting countries whose OECD EPS score is higher than the score scale's median.

$$EMC_{it} = \alpha + \beta_1 Ab_AP_{it} + \beta_2 Reg_High_{it} + \beta_3 \times Ab_AP_{it} \times Reg_High_{it} + \beta_4 Ab_Temp_{it} + \Sigma_t YearMonth_t + \epsilon_{it} \quad \text{Eq.(8)}$$

The coefficient of interest is β_3, which captures how the effect of abnormal air pollution differs across environmental policy regimes. This is represented by the coefficient of *Ab_AP* x *Reg_High* in Table 12. We are also interested specifically in months with the highest abnormal PM2.5 exposure in countries with strict environmental policies *(Ab_AP Q5* x *Reg_High*) and their effect on EMC returns.

Table 12: EMC portfolio return, abnormal air pollution (PM2.5), environmental regulation

Panel A: Equal-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.064		0.069			
	(1.49)		(1.46)			
Ab_AP Q2		0.381		-0.475	0.324	-0.058
		(1.03)		(-0.58)	(1.03)	(-0.90)
Ab_AP Q3		0.327		-0.476	0.277	-0.050
		(0.94)		(-0.49)	(1.06)	(-0.54)
Ab_AP Q4		0.185		-0.530	0.139	-0.046
		(0.68)		(-0.58)	(0.71)	(-0.56)
Ab_AP Q5		0.972		0.255	0.812	-0.161
		(1.53)		(0.26)	(1.48)	(-1.40)
Reg_High	-0.079	0.027	-0.013	-0.216	0.016	-0.011
	(-0.39)	(0.08)	(-0.04)	(-0.41)	(0.07)	(-0.13)
Ab_AP × Reg_High	-0.004		0.018			
	(-0.12)		(0.27)			
AP_AP Q5 * Reg_High		-0.032		0.057	-0.026	0.006
		(-0.30)		(0.31)	(-0.31)	(0.21)
Ab_Temp	0.060	0.046	-0.084	-0.110	0.036	-0.009
	(0.94)	(0.75)	(-1.23)	(-1.53)	(0.76)	(-0.60)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,475	1,475	1,475	1,475	1,475	1,475
Adj. R^2	0.023	0.022	0.008	0.006	0.019	0.027

Panel B: Value-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.092*		0.080**			
	(2.00)		(2.11)			
Ab_AP Q2		0.462		-0.661	0.513	0.052
		(1.01)		(-0.60)	(1.19)	(0.23)
Ab_AP Q3		0.590		-0.329	0.377	-0.214
		(1.56)		(-0.40)	(1.26)	(-1.01)
Ab_AP Q4		0.298		-0.298	0.311	0.013
		(0.66)		(-0.50)	(0.79)	(0.06)
Ab_AP Q5		1.061		0.223	0.769	-0.292
		(1.52)		(0.26)	(1.14)	(-0.90)
Reg_High	-0.105	-0.306	0.150	-0.174	-0.256	0.050
	(-0.55)	(-0.59)	(0.39)	(-0.29)	(-0.70)	(0.18)
Ab_AP × Reg_High	-0.010		0.013			
	(-0.15)		(0.15)			
AP_AP Q5 * Reg_High		0.079		0.107	0.032	-0.047
		(0.61)		(0.62)	(0.30)	(-0.60)
Ab_Temp	0.040	0.017	-0.152*	-0.185*	0.030	0.014
	(0.61)	(0.26)	(-1.73)	(-1.82)	(0.62)	(0.48)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,475	1,475	1,475	1,475	1,475	1,475
Adj. R^2	0.018	0.016	0.022	0.019	0.007	0.013

Note: The table presents results from regressions of EMC portfolio returns on abnormal air pollution (PM2.5) variables, controlling for abnormal temperature (Ab_Temp). EMISSION and CLEAN are formed based on firms' industry subsector codes. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. Reg_High is a dummy variable that takes the value of one if the environmental policy stringency score in the country is greater than 3.5 on a scale of 0–6. The sample ranges from January 2012 to December 2020, with 29 countries.In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

We do not observe environmental regulation affecting the relationship between abnormal PM2.5 exposure and EMC returns, and neither do we see the regulation itself affecting EMC returns. Controlling for regulation, we observe a small increase in value-weighted EMC size-adjusted return for each unit of abnormal PM2.5 exposure, primarily for larger cap stocks. At the 10% significance level, this is weak evidence that higher abnormal exposure drives small positive EMC returns. The combination of Q5 PM2.5 exposure and strict regulation has no effect on EMC returns. Similar results are obtained when re-estimating Eq.(7) with PM10 (Table 9A in the Appendix), with no observed effect of abnormal PM10 exposure on EMC returns, and no effect of environmental regulation on the aforementioned relationship. Overall, this offers no evidence that stringency of environmental regulation, when specified by the OECD EPS score, makes investors update their beliefs about firms' future cash flows. Therefore, findings in Table 6 are not driven by varying environmental regulation across our sample countries. Abnormal air pollution does not systematically affect *EMC* return in countries with a high-quality environmental regulatory system.

Climate change concern

We extend the analysis of Choi et al. (2020) and existing research on the financial effect of air pollution by analysing whether abnormal air pollution has an impact on stock return in periods with: (i) high climate change news coverage and (ii) negative climate change sentiment in news media. These variables capture, although not perfectly, shocks to climate change concern. As suggested by the findings of Pástor et al. (2022), the relative outperformance of green assets compared to brown assets in the past decade is driven by climate change concern shocks; such shocks influence investors' expectations about firm cash flows and preferences toward green versus brown assets. They find that shocks to climate change concern increases the attractiveness and price of green assets. Similarly, upon recognizing the effect of air pollution on climate change, people may stay away from climate-unfriendly stocks but prefer climate-friendly stocks, especially in months with abnormally high air pollution alongside elevated climate change concerns. We expect increased news coverage and lower sentiment to contribute to pollution's effect on *EMC* returns. Exposure to such news can lead investors to increase

their private perception of climate risk, thereby increasing their expectation of climate-sensitive firms facing environmental enforcement actions in the future, and thus expecting lower future cash flows, or given their non-pecuniary preferences shift away from climate-unfriendly firms.

In Table 13, we re-estimate Eq.(7) for equal-weighted *EMC* size-adjusted return by replacing Reg_High_{it} with dummy variables for high climate news coverage change (*High_CNCC*) and low climate news sentiment change (*Low_CNSC*).

Table 13: EMC portfolio return, PM2.5, Climate Change News

Panel A: Equal-weighted EMC returns, Climate Change News Coverage, News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.032		0.074**	
	(0.82)		(2.66)	
Ab_AP Q2		0.536		0.562
		(0.83)		(0.84)
Ab_AP Q3		0.308		0.346
		(0.77)		(0.81)
Ab_AP Q4		0.507		0.567
		(1.48)		(1.51)
Ab_AP Q5		0.521		0.647
		(1.19)		(1.11)
High_CNCC	-0.375*	0.052		
	(-1.73)	(0.13)		
Ab_AP × High_CNCC	-0.012			
	(-0.27)			
Ab_AP Q5 × High_CNCC		-0.129		
		(-1.38)		
Low_CNSC			-0.564*	0.287
			(-2.00)	(0.65)
Ab_AP × Low_CNSC			-0.091**	
			(-2.55)	
Ab_AP Q5 × Low_CNSC				-0.190
				(-1.39)
Ab_Temp	0.078**	0.083**	0.077**	0.082**
	(2.64)	(2.60)	(2.51)	(2.45)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,746	1,746	1,746	1,746
Adj. R^2	0.008	0.007	0.010	0.007

Panel B: Value-weighted EMC returns, Climate Change News Coverage and Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.086**		0.029	
	(2.86)		(0.71)	
Ab_AP Q2		0.201		0.038
		(0.40)		(0.08)
Ab_AP Q3		0.527		0.213
		(1.09)		(0.46)
Ab_AP Q4		0.944**		0.457
		(2.10)		(0.84)
Ab_AP Q5		0.888		0.252
		(1.37)		(0.33)
High_CNCC	-0.319	0.674		
	(-1.22)	(1.15)		
Ab_AP × High_CNCC	-0.066			
	(-1.68)			
Ab_AP Q5 × High_CNCC		-0.266		
		(-1.43)		
Low_CNSC			0.077	-0.178
			(0.20)	(-0.29)
Ab_AP × Low_CNSC			0.035	
			(0.65)	
Ab_AP Q5 × Low_CNSC				0.053
				(0.22)
Ab_Temp	-0.020	-0.023	-0.020	-0.023
	(-0.41)	(-0.46)	(-0.41)	(-0.47)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,746	1,746	1,746	1,746
Adj. R^2	0.016	0.015	0.016	0.013

Note: The table presents results from regressions of EMC returns on abnormal PM2.5 exposure, Ab_AP, controlling for abnormal temperature (Ab_Temp). In Columns 1–2, High_CNCC is a dummy variable that equals one if the month's climate news coverage, within each country, is high (Climate News Coverage Change is positive). In Columns 3–4, Low_CNSC is a dummy variable that equals one if the month, within each country, has negative climate change news (Climate News Sentiment Change is below the country's historical monthly median). Equal-weighted portfolio returns are presented in Panel A, while value-weighted returns are presented in Panel B. The sample runs from January 2017 to December 2024, including 22 countries. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

In Table 13 Panel A Columns 1 and 3, we observe negative effects of high climate change news coverage, *High_CNCC*, and low climate change news sentiment, *Low_CNSC*, on equal-weighted *EMC* size-adjusted return, suggesting that the *EMC* portfolio earns lower returns in months with high climate change news coverage and low climate change news sentiment, regardless of abnormal PM2.5 exposure, at the 10% significance level. The coefficient estimates of the *High_CNCC* interaction terms are insignificant, suggesting no reaction in *EMC* return to abnormal PM2.5 exposure alongside high climate change news. In Column 3, we find that the coefficient of *Ab_AP* × *Low_CNSC* is negative at the 5% significance level, suggesting the higher abnormal PM2.5 exposure reduces *EMC* return, made stronger by negative climate change news media. These findings disappear when considering value-weighted returns in Panel B, suggesting they were primarily driven by smaller cap stocks. We see when controlling for *High_CNCC*, abnormal PM2.5 exposure drives 9bps higher *EMC* returns and almost 1% higher *EMC* returns in Q4 exposure months, both at the 5% level. For PM10 (Table 10A in Appendix), we observe no reaction in *EMC* return to abnormal PM10 exposure, even in months with high climate change news coverage and low climate change news sentiment. However, *Low_CNSC* negatively affects equal-weighted *EMC* size-adjusted returns by 43bps, although this effect disappears when value-weighting, likely driven by smaller cap stocks. We also see larger cap stocks (value-weighting) offering 1.2%

higher return during Q5 exposure months, after controlling for high climate news coverage. Overall for climate change news, it may be smaller cap stocks that are negatively affected by negative sentiment, whereas larger cap stocks are positively affected by climate news coverage. However, we observe no systematic effect of abnormal air pollution on *EMC* return in months with high climate change concern, as proxied by extensive climate change news coverage and negative climate change news sentiment.

Air pollution salience

Building on the finding of Fisman, Ghosh, Sarkar and Zhang (2023) suggesting that investors are reacting to air pollution information, we investigate whether stock returns become more sensitive to air pollution when news reports of air pollution are elevated or when news about air pollution are negative. News media could serve as a channel through which the salience of the local experience of air pollution amplifies. This test is conducted by replicating the methodology applied to climate change news.

Table 14: EMC portfolio return, abnormal air pollution (PM2.5), Pollution News

Panel A: Equal-weighted EMC returns, Pollution News Coverage and News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.029		0.031	
	(0.86)		(1.04)	
Ab_AP Q2		0.460		0.412
		(0.66)		(0.66)
Ab_AP Q3		0.153		0.087
		(0.39)		(0.25)
Ab_AP Q4		0.259		0.162
		(1.03)		(0.46)
Ab_AP Q5		0.192		0.082
		(0.30)		(0.23)
High_PNCC	0.072	0.007		
	(0.36)	(0.01)		
Ab_AP × High_PNCC	-0.006			
	(-0.09)			
Ab_AP Q5 × High_PNCC		0.034		
		(0.19)		
Low_PNSC			-0.316	-0.550
			(-1.30)	(-1.21)
Ab_AP × Low_PNSC			-0.009	
			(-0.22)	
Ab_AP Q5 × Low_PNSC				0.088
				(0.97)
	(-0.09)			
Ab_Temp	0.075**	0.080**	0.076**	0.081**
	(2.47)	(2.49)	(2.48)	(2.61)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,746	1,746	1,746	1,746
Adj. R^2	0.007	0.006	0.008	0.007

Panel B: Value-weighted EMC returns, Pollution News Coverage and News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.050		0.057**	
	(1.15)		(2.20)	
Ab_AP Q2		-0.033		0.114
		(-0.07)		(0.25)
Ab_AP Q3		0.073		0.357
		(0.19)		(0.95)
Ab_AP Q4		0.248		0.664*
		(0.50)		(1.75)
Ab_AP Q5		-0.042		0.549
		(-0.06)		(1.02)
High_PNCC	0.025	-0.545		
	(0.09)	(-0.69)		
Ab_AP × High_PNCC	-0.005			
	(-0.05)			
Ab_AP Q5 × High_PNCC		0.198		
		(0.97)		
Low_PNSC			-0.264	0.060
			(-0.93)	(0.18)
Ab_AP × Low_PNSC			-0.017	
			(-0.53)	
Ab_AP Q5 × Low_PNSC				-0.087
				(-0.68)
Ab_Temp	-0.020	-0.024	-0.019	-0.023
	(-0.42)	(-0.49)	(-0.40)	(-0.47)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,746	1,746	1,746	1,746
Adj. R^2	0.015	0.014	0.016	0.014

Note: The table presents results from regressions of EMC returns on abnormal air pollution (PM2.5) variables, controlling for abnormal temperature (Ab_Temp). In Columns 1–2, High_PNCC is a dummy variable that equals one if the month's pollution news coverage, within each country, is high (Pollution News Coverage Change is positive). In Columns 3–4, Low_PNSC is a dummy variable that equals one if the month, within each country, has negative pollution news (Pollution Sentiment Change is below the country's historical monthly median). Equal-weighted portfolio returns are presented in Panel A, while value-weighted returns are presented in Panel B. The sample runs from January 2017 to December 2024, including 22 countries. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

We see in Table 14 that abnormal PM2.5 exposure increases value-weighted *EMC* size-adjusted returns by 6bps after controlling for low pollution news sentiment, *Low_PNSC*. For PM10 (Table 11A in Appendix), controlling for high pollution news coverage, *High_PNCC*, we see Q5 PM10 exposure driving 1.2% higher value-weighted *EMC* size-adjusted returns at the 5% significance level. However, we see no systematic pattern in how air pollution news coverage or sentiment affects the reaction in *EMC* returns to abnormal pollution.

5. Discussion

5.1 Analysis

Our first hypothesis predicted that abnormal air pollution would increase investors' attention to climate change, as measured by Google search activity on "global warming". Overall, we find limited evidence supporting this hypothesis. Abnormal PM2.5 and PM10 levels do not consistently lead to higher climate-related search intensity across European exchange cities. City-level Google search activity related to climate change tends to be lower during periods of elevated PM2.5 exposure. The results suggest that higher concentrations of fine particulate matter do not function as a wake-up call for climate change. This finding further challenges the idea that PM2.5 shocks lead investors to update their beliefs about climate risk. This result deviates from our initial expectations and from findings in closely related studies, such as Choi et al. (2020), who show that unusually high local temperatures significantly increase attention to global warming.

The second hypothesis posited that abnormal air pollution would lead to the underperformance of brown stocks relative to green stocks. Empirically, our analysis reveals inconsistent results across pollutants, specifications, and portfolio constructions. Overall, abnormal PM2.5 does not drive meaningful or consistent effects on emissions-minus-clean (EMC) portfolio returns. In contrast, PM10 shows somewhat stronger, though still inconsistent, effects. PM10 is associated with lower attention trends at the country level during periods of elevated PM10 exposure relative to periods of low PM10 exposure and produces more return responses than PM2.5 in some specifications.This divergence underscores the importance of distinguishing between PM2.5 and PM10 when analysing their financial impact. While both pollutants are linked to climate change, PM2.5 generally produces fewer significant results than PM10, likely reflecting differences in salience and perceptibility.

The finding of no consistent, systematic pattern in how abnormal air pollution affects the relative stock performance of brown versus green firms can be compared to the study of Fisman, Ghosh, Sarkar, and Zhang (2023), which shows that providing explicit information about local air quality negatively affects retail investors' investments into brown stocks. Their results emphasize the role of information disclosure rather than physical exposure. By contrast, our study focuses on actual experiences of abnormal air pollution, rather than increased access to pollution data. The difference in findings suggests that information disclosure plays a crucial role. While pollution information can directly shift beliefs and investment behavior, pollution exposure alone may not be sufficient to update climate change beliefs.

The results are not uniform across portfolio construction methods, pollution quintiles, and industries. There are inconsistencies between equal-weighted and value-weighted *EMC* returns, implying that the relationships we investigate may vary over market cap. For instance, as documented by Pástor et al. (2022), smaller stocks exhibit a more slow reaction to climate shocks. We observe stronger responses among large-cap firms, consistent with evidence that larger firms react more to current climate shocks, while smaller firms respond more to past shocks (Pástor et al., 2022). This size heterogeneity may explain part of the inconsistency in our results. Another possible explanation is that green assets may only outperform brown assets during periods when

climate-related stocks sufficiently and unexpectedly strengthen climate concerns (Pástor et al., 2022; Ardia et al., 2022). If pollution episodes in our sample are not perceived as "big shocks," or do not pose significant risk to firms and investors, investor attention may remain low, limiting their impact on climate-sensitive portfolios. This interpretation is consistent with research showing that investor attention is often triggered by salient, extreme events rather than incremental changes.

Taken together, our findings highlight both the limits and the potential channels through which pollution may affect financial markets. While PM10 appears more salient and produces stronger return responses, PM2.5 does not consistently generate effects. The inconsistencies across weighting methods, industries, and quintiles suggest that pollution shocks alone may not be sufficient to shift capital allocation toward or away from climate-sensitive firms. Instead, the interaction of pollution salience, firm size, and shock magnitude appears critical. Our contribution lies in documenting these limits and suggesting that pollution episodes, unlike temperature shocks, do not reliably serve as catalysts for climate-conscious capital allocation.

Finally, the findings suggest that not all environmental shocks are equally effective in shaping investor beliefs or asset prices. While air pollution is highly salient in daily life, it may primarily operate through local health and mood channels rather than through climate-risk belief updating. In addition, our results highlight the limits of relying on personal environmental experiences to drive climate-related financial reallocation. This may help explain why markets remain slow to price certain climate risks, consistent with evidence of underreaction to slow-moving environmental risks (Hong, Li, and Xu, 2019).

5.2 Limitations

There are several limitations to this study. First, we cannot observe the physical location of investors nor their actual exposure to abnormal air pollution. Trading activity may be conducted by investors who are not directly exposed to local air pollution, which could attenuate the estimated effects.

Second, in an ideal scenario, future research would incorporate investor-level data to disentangle how attention and trading behavior vary across investor types. Prior studies show that institutional investors, retail investors, and blockholders exhibit distinct sensitivities to environmental signals. For example, institutional investors may overreact to salient natural disasters (Alok, Kumar, and Wemers, 2020), while blockholders, often located in exchange cities, may be more directly exposed to local pollution shocks, and often act as buyers of last resort (Choi et al., 2020). As our analysis does distinguish between investor types, there is a risk of attenuated effects.

Our results also vary across time periods and quintile specifications, underscoring the instability of pollution effects in financial markets. Inconsistent findings across abnormal pollution quintiles suggest that investor responses may not scale linearly with pollution intensity. Instead, attention and return effects appear sporadic, raising questions about whether pollution shocks are sufficiently salient to trigger systematic capital reallocation.

Finally, our focus on Europe raises both strengths and limitations. On one hand, the European Union is characterized by higher climate awareness and stronger public support for climate action (European Commission, 2025). This may confound our results, as investor attention could be driven more by country-level awareness and policy discourse than by local pollution shocks. On the other hand, this context provides a unique opportunity to study how pollution interacts with markets in a region where climate salience is already high. Whether our findings generalize beyond Europe remains an open question, and future work should examine cross-country heterogeneity to assess robustness.

6. Concluding Remarks

This study examines whether abnormal local air pollution acts as a wake-up call to climate change and whether such shocks affect the relative performance of brown and green firms in European stock markets. Using data from different European exchange cities between 2012 and 2024, we analyze the impact of PM2.5 and PM10 on investor attention and stock return.

Overall, we find limited evidence that abnormal air pollution increases attention to climate change or leads to systematic underperformance of brown stocks relative to green stocks. These findings suggest that air pollution shocks may not constitute strong belief-updating events about climate risks in the European context.

Our results contribute to the climate finance literature by highlighting the importance of the channel through which environmental information reaches investors. However, future research could extend this work in several directions. First, studying regions with lower baseline climate concern or more severe pollution, such as emerging markets, may provide stronger tests of the pollution-as-salience mechanism. However, our findings highlight the importance of accounting for industry effects in order to isolate any financial effect of air pollution. This may be achieved by using industry-adjusted definitions of brown and green firms, or other sources of exogenous variation in air pollution (e.g., sudden policy changes or plant closures). Then, combining pollution data with investor-level location and trading data could help better identify behavioral channels.

More broadly, understanding which experiences truly shift beliefs about climate risk remains crucial for both asset pricing and policy design. As climate change intensifies, identifying the conditions under which markets internalize environmental risks will become increasingly important.

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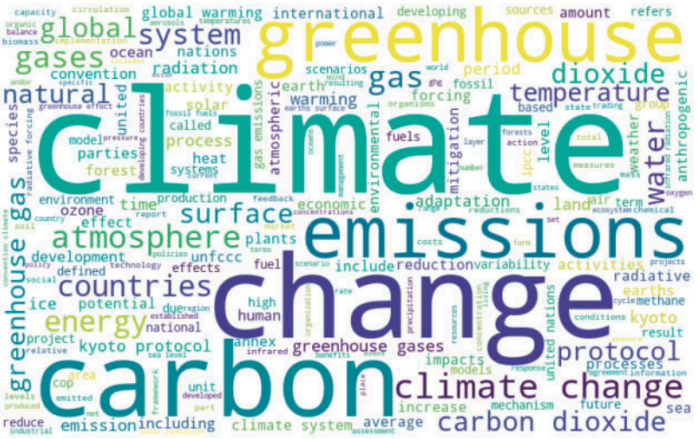
Appendix

This Appendix includes figures, tables, and charts mentioned previously in the main text.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earth
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weather
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total
measures

$RET(EMISSION)$	*EMISSION* portfolio return calculated using size-adjusted stock returns
$RET(CLEAN)$	*CLEAN* portfolio return calculated using size-adjusted stock returns
$EMC_{t+1,t+3}$	Size-adjusted *EMC* portfolio return over the months *t+1* to *t+3*
$EMC_{t+1,t+6}$	Size-adjusted *EMC* portfolio return over the months *t+1* to *t+6*
$EMC_{t+1,t+12}$	Size-adjusted *EMC* portfolio return over the months *t+1* to *t+12*
AP_{it}	Air pollution in month *t* for city *i*, calculated using the city's daily air pollution levels
Avg_AP_{it}	Average monthly air pollution for city *i* over the 120 months prior to month *t*
Mon_AP_{it}	Average deviation of this month's air pollution from the average monthly air pollution for city *i* over the 120 months prior to month *t*
Ab_AP_{it}	Abnormal air pollution in month *t* for city *i*
$Ab_AP_{it}\ Q1–Q5$	Abnormal air pollution that equal to one if the month belongs to quintiles 1–5, respectively. $Ab_AP_{it}\ Q1$ is the least polluted quintile, whereas $Ab_AP_{it}\ Q5$ is the most polluted quintile.
Ab_Temp_{it}	Abnormal temperature in month *t* for city *i*
Reg_Score_{it}	Environmental policy stringency (EPS) score in month *t* for country of city *i*
Reg_High_{it}	Dummy variable taking the value of one for countries whose EPS score is above 3.5
$Climate\ News\ Coverage\ Change_{it}$	Log change in the total number of climate change news articles published in country of city *i* on month *t*, adjusted for seasonality
$High_CNCC_{it}$	Dummy variable taking the value of one for months, within country of city *i*, with a positive *Climate News Coverage Change*
$Climate\ News\ Sentiment\ Change_{it}$	Shock in the average tone of climate change news articles published in country of city *i* on month *t*
Low_CNSC_{it}	Dummy variable taking the value of one for months, within country of city *i*, with a *Climate News Sentiment Change* below the city's historical monthly median

$Pollution\ News\ Coverage\ Change_{it}$	Log change in the total number of air pollution news articles published in country of city *i* on month *t*, adjusted for seasonality
$High_PNCC_{it}$	Dummy variable taking the value of one for months, within country of city *i*, with a positive *Pollution News Coverage Change*
$Pollution\ News\ Sentiment\ Change_{it}$	Shock in the average tone of air pollution news articles published in country of city *i* on month *t*
Low_PNSC_{it}	Dummy variable taking the value of one for months, within country of city *i*, with a *Pollution News Sentiment Change* below the city's historical monthly median

Note: The table defines all variables of the study.

Table 2A: List of European countries and cities

Country	City
Austria	Amsterdam
Belgium	Athens
Bosnia Herzegovina	Banja Luka
Bulgaria	Barcelona
Croatia	Belgrade
Cyprus	Berlin
Czech Republic	Bilbao
Denmark	Bologna
Estonia	Bratislava
Finland	Brussels
France	Bucharest
Germany	Budapest
Greece	Copenhagen
Hungary	Dublin
Iceland	Düsseldorf
Ireland	Frankfurt am Main
Italy	Hamburg
Latvia	Hannover
Lithuania	Helsinki
Luxembourg	Kyiv
Macedonia	Lisbon
Malta	Ljubljana
Montenegro	London
Netherlands	Luxembourg City
Norway	Madrid
Poland	Milan
Portugal	Moscow
Romania	Munich
Russia	Nicosia
Serbia	Oslo
Slovak Republic	Paris
Slovenia	Podgorica
Spain	Prague
Spain	Reykjavik
Sweden	Riga
Switzerland	Sarajevo
Ukraine	Skopje
United Kingdom	Sofia
	Stockholm
	Stuttgart
	Tallinn
	Valencia
	Valletta
	Vienna
	Vilnius
	Warsaw
	Zagreb
	Zurich

Note: The table reports the countries and cities of stock market exchanges that are defined as “Europe” by DataStream.

Table 3A: Sample construction based on PM10

Sample	Number of observations	Number of locations
Main sample X	3,239	36 cities & 32 countries
X merged with MSCI	351	5 cities
X merged with EPS score	1,423	22 countries
X merged with climate and pollution news data	1,746	20 countries

Note: The table shows the construction of the different samples, with the main sample, X, being merged on PM10 data.

Table 4A: Summary statistics (with PM10)

Panel A: Initial sample

Variable	Obs	Mean	Std. Dev.	Min	Max	P10	P25	P50	P75	P90
Ab_AP (PM10)	3490	-4.086	7.583	-52.396	64.455	-11.985	-7.393	-3.637	-.598	3.014
DSVI(city)	5616	-.446	71.694	-352.182	371.149	-52.036	-21.266	0	19.595	54.62
DSVI(country)	4992	-.562	69.624	-453.732	499.452	-48.213	-20.647	0	18.802	47.747
Equal-Weighted EMC(adj)	5248	.013	6.03	-121.092	95.393	-4.677	-1.861	0	1.823	4.598
Equal-Weighted EMC(raw)	5248	.099	9.481	-190.268	180.486	-6.375	-2.543	-.016	2.538	6.575
Equal-Weighted EMISSION	5254	.001	4.19	-90.819	81.084	-3.381	-1.351	0	1.294	3.328
Equal-Weighted CLEAN	5608	-.011	2.353	-57.718	45.418	-1.041	-.381	0	.389	1.073
Equal-Weighted EMC(t+1,t+3)	5248	.003	7.458	-54.384	91.294	-7.443	-3.115	0	3.173	7.436
Equal-Weighted EMC(t+1,t+6)	5248	-.016	10.513	-74.306	94.453	-10.98	-4.576	0	4.844	11.293
Equal-Weighted EMC(t+1,t+12)	5248	-.009	15.68	-94.039	94.707	-17.167	-6.975	0	7.663	16.786
Value-Weighted EMC(adj)	5248	.009	6.379	-96.972	69.271	-6.287	-2.614	0	2.59	6.107
Value-Weighted EMC(raw)	5248	-.03	9.528	-201.598	121.863	-7.593	-3.413	-.17	3.196	7.538
Value-Weighted EMISSION	5254	-.04	4.528	-90.819	61.15	-4.342	-1.829	0	1.779	4.333
Value-Weighted CLEAN	5608	-.068	3.395	-55.042	33.171	-2.697	-.94	0	1.005	2.609
Value-Weighted EMC(t+1,t+3)	5248	.007	9.696	-60.182	96.872	-10.088	-4.682	0	4.154	10.412
Value-Weighted EMC(t+1,t+6)	5248	.014	14.115	-79.353	174.51	-14.907	-6.812	0	6.498	15.133
Value-Weighted EMC(t+1,t+12)	5248	.004	21.045	-112.293	190.859	-22.784	-10.115	0	9.555	21.515
Ab_Temp	5609	.623	3.093	-12.225	14.169	-3.161	-1.347	.621	2.628	4.53
Reg_Score	2484	3.215	.741	.722	4.889	2.5	2.889	3.222	3.722	4.028
Climate News Coverage Change	3420	0	25.106	-207.089	104.45	-30.491	-15.723	-.227	15.884	30.47
Cimate News Sentiment Change	3420	.012	.543	-4.827	4.1	-.599	-.277	.032	.313	.587
Pollution News Coverage Change	3420	0	29.562	-151.654	172.411	-37.173	-19.124	-.062	18.982	37.113
Pollution News Sentiment Change	3420	.008	.989	-4.503	6.061	-1.138	-.547	.007	.547	1.206

Panel B: Final sample (equal-weighted EMC returns)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
EMC(adj)	3239	.1	5.777	-4.124	-1.663	0	1.585	4.225
EMC(raw)	3239	.217	9.754	-6.307	-2.508	-.002	2.453	6.584
EMISSION	3239	.053	3.828	-2.955	-1.186	0	1.103	3.006
CLEAN	3239	-.048	2.73	-1.042	-.382	0	.38	1.077
EMC(t+1,t+3)	3239	.148	7.176	-6.461	-2.674	0	2.904	6.995
EMC(t+1,t+6)	3239	.294	10.07	-9.631	-3.913	0	4.474	10.719
EMC(t+1,t+12)	3239	.643	14.745	-14.433	-5.87	0	7.271	16.448

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
DSVI(city)	3483	-.362	73.998	-53.462	-21.102	0	19.878	54.175
DSVI(country)	3147	-.469	72.242	-48.332	-21.242	0	19.401	47.801
Aver_AP	3483	27.092	8.406	15.904	19.953	27.413	32.643	37.103
Mon_AP	3483	.384	7.415	-8.257	-3.569	-.201	3.79	8.674
Ab_AP	3483	-4.087	7.589	-12	-7.401	-3.64	-.585	3.017
Ab_Temp	3483	.632	3.092	-3.179	-1.337	.64	2.658	4.517

Panel C: Final sample (value-weighted EMC returns)

Variable	Obs	Mean	Std. Dev.	P10	P25	P50	P75	P90
EMC(adj)	3239	-.01	5.745	-5.566	-2.318	0	2.237	5.585
EMC(raw)	3239	-.047	9.321	-7.391	-3.36	-.254	3.023	7.589
EMISSION	3239	-.051	4.092	-3.961	-1.606	0	1.503	3.898
CLEAN	3239	-.041	3.016	-2.503	-.891	0	.988	2.5
Ab_Temp	3239	.622	3.067	-3.161	-1.347	.623	2.639	4.479

Note: The table presents the summary statistics for the independent and dependent variables employed in the main analyses. Ab_AP (PM10) denotes abnormal air pollution measured by PM10. DSVI denotes the monthly

logarithmic change in Google SVI of the topic "global warming", measured at both city and country levels. Portfolio return, expressed in percentage term, is calculated as the average raw or size-adjusted return of stocks in month t, using equal or value weights. Size-adjusted return is computed as the raw return minus the average return of stocks in the same size quintile by each exchange. The portfolios EMISSION and CLEAN are constructed based on firms' industry subsector classifications, with high-carbon industries defined according to the IPCC classification. EMC equals EMISSION minus CLEAN. EMC(adj) is calculated using size-adjusted returns; EMC(raw) is calculated using raw returns. Ab_Temp denotes abnormal temperature. Climate News Coverage Change and Pollution News Coverage Change are the monthly log changes in the number of climate change and air pollution news articles, respectively. Climate News Sentiment Change and Pollution News Sentiment Change are the shocks in the monthly average tone of climate change and air pollution news articles, respectively.

Table 5A: Matching of industries based on SIC Industry Name and ICB Subsector Name

SIC Code	SIC Industry Name	ICB Code	ICB Subsector Name
Biotech			
2833	MEDICINAL CHEMICALS & BOTANICAL PRODUCTS	55201020	Specialty Chemicals
8050	SERVICES-NURSING & PERSONAL CARE FACILITIES	20101010	Health Care Facilities
2834	PHARMACEUTICAL PREPARATIONS	20103015	Pharmaceuticals
8082	SERVICES-HOME HEALTH CARE SERVICES	20101025	Health Care Services
3841	SURGICAL & MEDICAL INSTRUMENTS & APPARATUS	20102010	Medical Equipment
2836	BIOLOGICAL PRODUCTS, (NO DISGNOSTIC SUBSTANCES)	20103010	Biotechnology
8090	SERVICES-MISC HEALTH & ALLIED SERVICES, NEC	20101030	Health Care: Misc.
Telecom			
4812, 4813, 4822	RADIOTELEPHONE COMMUNICATIONS, TELEPHONE COMMUNICATIONS (NO RADIOTELEPHONE), TELEGRAPH & OTHER MESSAGE COMMUNICATIONS	15102015	Telecommunications Services
3661	TELEPHONE & TELEGRAPH APPARATUS	15101010	Telecommunications Equipment
4841	CABLE & OTHER PAY TELEVISION SERVICES	15102010	Cable Television Services
Computers			
7370, 7371, 7373	COMPUTER SERVICES	10101010	Computer Services
5094	WHOLESALE-JEWELRY, WATCHES, PRECIOUS STONES & METALS	55103030	Platinum and Precious Metals
5045	WHOLESALE-COMPUTERS & PERIPHERAL EQUIPMENT & SOFTWARE	10101015	Software
3571	ELECTRONIC COMPUTERS	10102030	Computer Hardware
Electronics			
3670	ELECTRONIC COMPONENTS & ACCESSORIES	10102015	Electronic Components
3670	ELECTRONIC COMPONENTS & ACCESSORIES	50202010	Electrical Components
3670	ELECTRONIC COMPONENTS & ACCESSORIES	10102010	Semiconductors
3600	ELECTRONIC & OTHER ELECTRICAL EQUIPMENT	10102035	Electronic Office Equipment
3600	ELECTRONIC & OTHER ELECTRICAL EQUIPMENT	50202025	Electronic Equipment: Gauges and Meters
3600	ELECTRONIC & OTHER ELECTRICAL EQUIPMENT	50202030	Electronic Equipment: Pollution Control
3600	ELECTRONIC & OTHER ELECTRICAL EQUIPMENT	50202040	Electronic Equipment: Other
3600	ELECTRONIC & OTHER ELECTRICAL EQUIPMENT	50202020	Electronic Equipment: Control and Filter

Notes: The table shows the matching process for categorizing ICB Subsectors into harmed "innovative" industries, or non-harmed "non-innovative" industries. The industries categorized as harmed include those with the following SIC Codes: 8050, 2834, 5045, 3670, and 3600, following Ouimet and Zarutskie (2014).

Table 6A: Long-term EMC returns subsequent to abnormal pollution (PM10)

Panel A: Equal-weighted EMC returns

	(1) EMC(adj, t+1,t+3)	(2) EMC(adj, t+1,t+3)	(3) EMC(adj, t+1,t+6)	(4) EMC(adj, t+1,t+6)	(5) EMC(adj, t+1,t+12)	(6) EMC(adj, t+1,t+12)
Ab_AP	0.015		0.011		0.035	
	(0.87)		(0.29)		(0.48)	
Ab_AP Q2		0.054		-0.088		0.868
		(0.11)		(-0.10)		(0.83)
Ab_AP Q3		0.400		0.329		1.027
		(0.70)		(0.39)		(0.78)
Ab_AP Q4		0.032		-0.215		0.208
		(0.07)		(-0.28)		(0.19)
Ab_AP Q5		0.703		0.791		1.816
		(1.43)		(0.81)		(1.30)
Ab_Temp	0.040	0.033	0.000	-0.010	0.135	0.123
	(0.69)	(0.58)	(0.00)	(-0.09)	(0.67)	(0.62)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,239	3,239	3,239	3,239	3,239	3,239
Adj. R^2	0.015	0.015	0.019	0.019	0.030	0.030

Panel B: Value-weighted EMC returns

	(1) EMC(adj, t+1,t+3)	(2) EMC(adj, t+1,t+3)	(3) EMC(adj, t+1,t+6)	(4) EMC(adj, t+1,t+6)	(5) EMC(adj, t+1,t+12)	(6) EMC(adj, t+1,t+12)
Ab_AP	0.014		0.028		0.053	
	(0.54)		(0.38)		(0.47)	
Ab_AP Q2		0.404		0.360		0.783
		(0.71)		(0.42)		(0.82)
Ab_AP Q3		1.112		1.756		2.068
		(1.57)		(1.43)		(1.17)
Ab_AP Q4		-0.056		-0.021		0.280
		(-0.11)		(-0.02)		(0.15)
Ab_AP Q5		0.800		1.301		1.375
		(1.21)		(0.90)		(0.69)
Ab_Temp	-0.058	-0.058	-0.183	-0.186	-0.056	-0.051
	(-0.70)	(-0.71)	(-0.98)	(-1.02)	(-0.19)	(-0.19)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,239	3,239	3,239	3,239	3,239	3,239
Adj. R^2	0.010	0.011	0.020	0.022	0.018	0.018

Notes: The table presents regression results of EMC(t+1, t+3), EMC(t+1, t+6), and EMC(t+1,t+12) on abnormal air pollution (PM10) variables at month t and controls for abnormal temperature (Ab_Temp). EMC(t+1, t+3), EMC(t+1, t+6) are calculated using the equal-weighted or value-weighted average of size-adjusted stock returns over months t+1 to t+3, t+1 to t+6, and t+1 to t+12.. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. The sample ranges from January 2012 to December 2024, with 33 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Table 7A: EMC portfolio return, abnormal air pollution (PM10), MSCI

	Equal-weighted EMC(adj)		Value-weighted EMC(adj)	
	(1)	(2)	(3)	(4)
Ab_AP	-0.075		-0.103	
	(-1.91)		(-0.81)	
Ab_AP Q2		-0.444		1.904
		(-0.62)		(1.99)
Ab_AP Q3		-0.335		1.116
		(-0.91)		(0.52)
Ab_AP Q4		-0.572		0.589
		(-0.98)		(0.50)
Ab_AP Q5		-0.987		-0.955
		(-1.60)		(-0.65)
Ab_Temp	0.400**	0.422**	-0.158	-0.026
	(3.41)	(3.60)	(-0.45)	(-0.07)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	351	351	343	343
Adj. R^2	0.273	0.263	0.149	0.152

Note: The table presents results from regressions of EMC size-adjusted returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN, with EMISSION including stocks with MSCI carbon emission scores lower than 3 and CLEAN including stocks with scores higher than 7. Portfolio returns, expressed as percentages, are equal-weighted (Columns 1 and 2) and value-weighted (Columns 3 and 4). The sample ranges from January 2012 to December 2022, with 5 exchange cities. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1% levels.

Table 8A: EMC portfolio return, abnormal air pollution (PM2.5), Energy vs. Non-energy

Panel A: Equal-weighted EMC returns

	Energy		Non-energy	
	(1)	(2)	(3)	(4)
Ab_AP	-0.055		0.017	
	(-1.36)		(0.80)	
Ab_AP Q2		0.955		0.348
		(1.15)		(0.75)
Ab_AP Q3		0.845		0.287
		(1.14)		(0.99)
Ab_AP Q4		-0.802		0.306
		(-1.00)		(1.10)
Ab_AP Q5		-0.915		0.249
		(-1.63)		(0.56)
Ab_Temp	0.007	0.026	0.063*	0.065*
	(0.06)	(0.22)	(2.02)	(1.97)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,365	1,365	2,809	2,809
Adj. R^2	0.080	0.082	0.011	0.010

Panel B: Value-weighted EMC returns

	Energy		Non-energy	
	(1)	(2)	(3)	(4)
Ab_AP	-0.027		0.031	
	(-0.61)		(1.21)	
Ab_AP Q2		0.398		-0.071
		(0.44)		(-0.18)
Ab_AP Q3		1.119		0.276
		(1.29)		(0.78)
Ab_AP Q4		-1.128		0.292
		(-1.69)		(0.78)
Ab_AP Q5		-0.980		0.254
		(-1.12)		(0.51)
Ab_Temp	0.053	0.070	0.035	0.031
	(0.57)	(0.77)	(0.82)	(0.71)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,365	1,365	2,809	2,809
Adj. R^2	0.064	0.067	0.006	0.005

Note: The table shows results from regressions of EMC size-adjusted returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). EMC equals EMISSION minus CLEAN. The EMISSION portfolio is divided by Energy and Non-energy firms, and EMC portfolio returns are calculated for each group. Panel A presents equal-weighted portfolio returns and Panel B presents value-weighted returns. The sample ranges from January 2012 to December 2024, with 36 exchange cities. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels.

Chart 1: Permutation test for Table 3 (PM2.5)

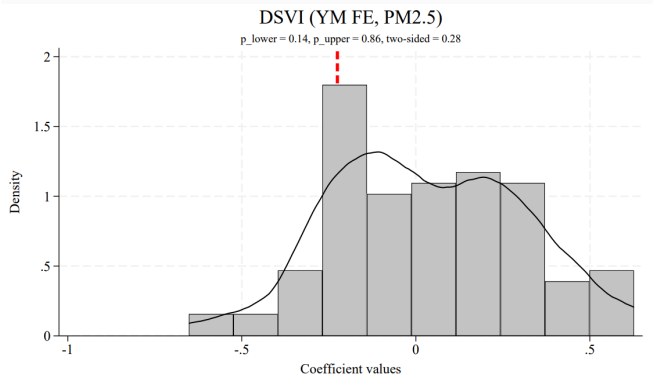

Chart 2: Permutation test for Table 4 (PM10)

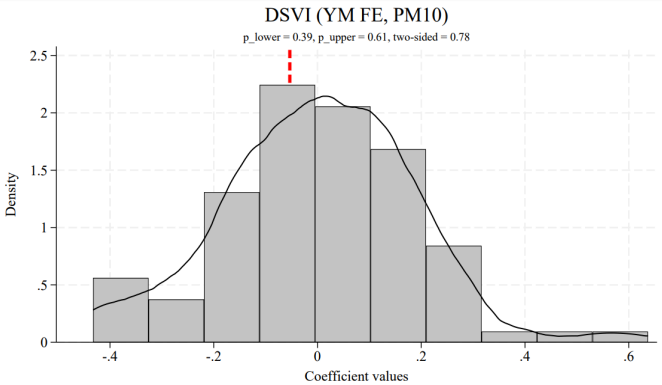

Chart 3: Permutation test for Table 5, Panel A (PM2.5)

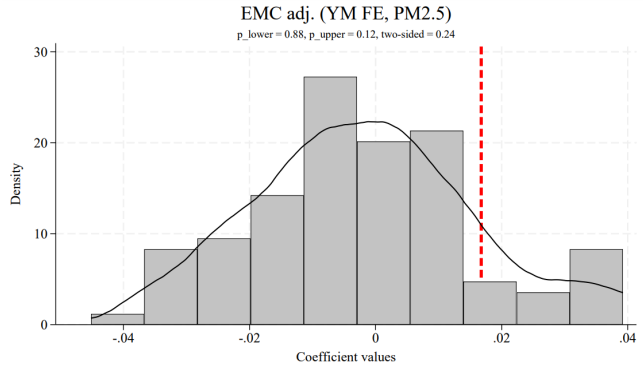

Chart 4: Permutation test for Table 6, Panel A (PM10)

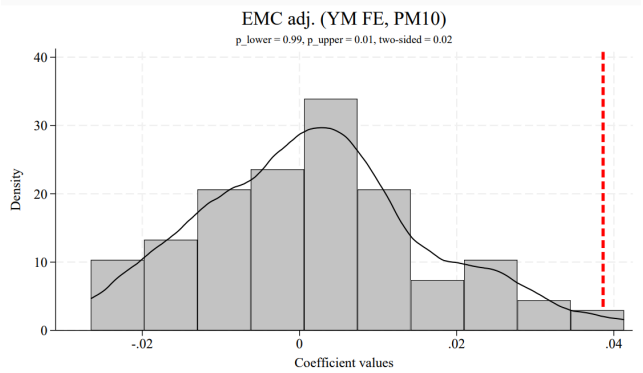

Chart 5: Permutation test for Table 5, Panel B (PM2.5)

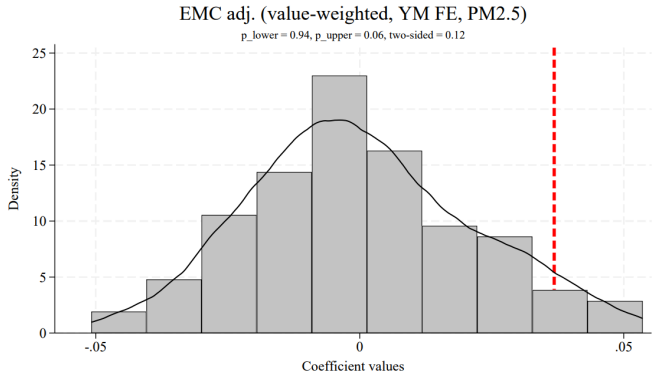

Chart 6: Permutation test for Table 6, Panel B (PM10)

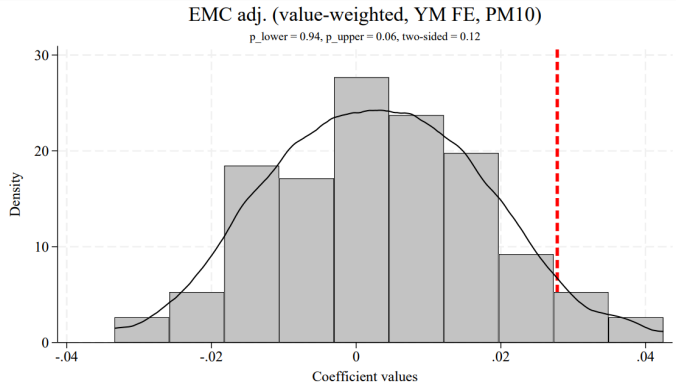

Table 9A: EMC portfolio return, abnormal air pollution (PM10), Environmental regulation

Panel A: Equal-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.008		0.024			
	(0.29)		(0.56)			
Ab_AP Q2		-0.115		-1.363	-0.102	0.013
		(-0.32)		(-1.28)	(-0.34)	(0.19)
Ab_AP Q3		0.262		0.644	0.215	-0.048
		(0.53)		(0.72)	(0.52)	(-0.49)
Ab_AP Q4		0.237		-0.094	0.204	-0.033
		(0.39)		(-0.09)	(0.41)	(-0.27)
Ab_AP Q5		-0.217		-0.233	-0.240	-0.024
		(-0.44)		(-0.20)	(-0.64)	(-0.20)
Reg_High	-0.040	-0.412	-0.070	-0.183	-0.363	0.049
	(-0.23)	(-0.91)	(-0.18)	(-0.30)	(-0.99)	(0.50)
Ab_AP × Reg_High	0.012		0.001			
	(0.45)		(0.02)			
AP_AP Q5 * Reg_High		0.109		0.032	0.097	-0.012
		(0.76)		(0.13)	(0.85)	(-0.35)
Ab_Temp	0.077	0.071	-0.054	-0.082	0.057	-0.015
	(0.99)	(0.95)	(-0.56)	(-0.82)	(0.95)	(-0.79)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,423	1,423	1,423	1,423	1,423	1,423
Adj. R^2	0.008	0.008	-0.003	0.004	0.006	0.015

Panel B: Value-weighted EMC returns

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(raw)	(4) EMC(raw)	(5) EMISSION	(6) CLEAN
Ab_AP	0.026		0.073			
	(1.01)		(1.33)			
Ab_AP Q2		0.513		-0.807	-0.024	-0.537
		(1.07)		(-0.62)	(-0.08)	(-1.32)
Ab_AP Q3		0.789		0.969	0.332	-0.457
		(1.49)		(1.00)	(0.77)	(-1.29)
Ab_AP Q4		1.041		0.722	0.625	-0.416
		(1.52)		(0.68)	(1.02)	(-0.99)
Ab_AP Q5		0.623		0.934	0.225	-0.398
		(1.01)		(0.85)	(0.49)	(-1.21)
Reg_High	0.100	-0.283	-0.072	0.458	-0.545	-0.262
	(0.42)	(-0.45)	(-0.16)	(0.48)	(-1.17)	(-0.84)
Ab_AP × Reg_High	0.024		-0.039			
	(0.61)		(-0.48)			
AP_AP Q5 * Reg_High		0.101		-0.132	0.143	0.041
		(0.55)		(-0.40)	(1.01)	(0.41)
Ab_Temp	0.068	0.060	-0.115	-0.152	0.049	-0.010
	(0.90)	(0.81)	(-1.16)	(-1.36)	(0.81)	(-0.38)
Year × Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	1,423	1,423	1,423	1,423	1,423	1,423
Adj. R^2	0.008	0.010	0.013	0.015	0.015	-0.005

Note: The table presents results from regressions of EMC portfolio returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). EMISSION and CLEAN are formed based on firms' industry subsector codes. Panel A reports equal-weighted portfolio returns and Panel B reports value-weighted returns. Reg_High is a dummy variable that takes on the value of one if the environmental policy stringency score in the country is greater than 3.5 on a scale of 0–6. The sample ranges from January 2012 to December 2020, with 29 countries.In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

Table 10A: EMC portfolio return, abnormal air pollution (PM10), Climate Change News

Panel A: Equal-weighted EMC returns, Climate Change News Coverage, News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.022		0.019	
	(0.80)		(0.73)	
Ab_AP Q2		-0.096		-0.120
		(-0.20)		(-0.25)
Ab_AP Q3		-0.355		-0.370
		(-0.46)		(-0.46)
Ab_AP Q4		-0.395		-0.469
		(-0.54)		(-0.61)
Ab_AP Q5		-0.060		-0.130
		(-0.08)		(-0.20)
High_CNCC	-0.598	-0.945		
	(-1.46)	(-1.39)		
Ab_AP × High_CNCC	0.016			
	(0.65)			
Ab_AP Q5 × High_CNCC		0.090		
		(0.58)		
Low_CNSC			-0.430*	-0.934
			(-1.80)	(-1.31)
Ab_AP × Low_CNSC			0.021	
			(0.68)	
Ab_AP Q5 × Low_CNSC				0.136
				(0.78)
Ab_Temp	0.071*	0.071*	0.067*	0.067
	(1.98)	(1.76)	(1.76)	(1.56)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,852	1,852	1,852	1,852
Adj. R^2	-0.000	-0.003	-0.001	-0.003

Panel B: Value-weighted EMC returns, Climate Change News Coverage and Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.047		0.002	
	(1.14)		(0.05)	
Ab_AP Q2		0.447		0.261
		(0.98)		(0.54)
Ab_AP Q3		0.573		0.227
		(0.89)		(0.33)
Ab_AP Q4		0.571		0.008
		(0.82)		(0.01)
Ab_AP Q5		1.232*		0.482
		(1.82)		(0.65)
High_CNCC	-0.431	0.218		
	(-1.03)	(0.30)		
Ab_AP × High_CNCC	-0.012			
	(-0.34)			
Ab_AP Q5 × High_CNCC		-0.188		
		(-1.00)		
Low_CNSC			0.374	-0.547
			(0.82)	(-0.89)
Ab_AP × Low_CNSC			0.074	
			(1.57)	
Ab_AP Q5 × Low_CNSC				0.204
				(0.84)
Ab_Temp	-0.021	-0.023	-0.022	-0.023
	(-0.36)	(-0.39)	(-0.40)	(-0.40)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,852	1,852	1,852	1,852
Adj. R^2	0.007	0.005	0.008	0.004

Note: The table presents results from regressions of EMC returns on abnormal PM10 exposure, Ab_AP, controlling for abnormal temperature (Ab_Temp). In Columns 1–2, High_CNCC is a dummy variable that equals one if the month's climate news coverage, within each country, is high (Climate News Coverage Change is positive). In Columns 3–4, Low_CNSC is a dummy variable that equals one if the month, within each country, has negative climate change news (Climate News Sentiment Change is below the country's historical monthly median). Equal-weighted portfolio returns are presented in Panel A, while value-weighted returns are presented in Panel B.

The sample runs from January 2017 to December 2024, including 22 countries. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.

Table 11A: EMC portfolio return, abnormal air pollution (PM10), Pollution News

Panel A: Equal-weighted EMC returns, Pollution News Coverage and News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.036		0.043	
	(1.55)		(1.48)	
Ab_AP Q2		-0.042		-0.094
		(-0.11)		(-0.20)
Ab_AP Q3		-0.245		-0.359
		(-0.42)		(-0.44)
Ab_AP Q4		-0.276		-0.422
		(-0.60)		(-0.58)
Ab_AP Q5		0.136		-0.074
		(0.27)		(-0.10)
High_PNCC	-0.200	-0.164		
	(-0.78)	(-0.34)		
Ab_AP × High_PNCC	-0.012			
	(-0.30)			
Ab_AP Q5 × High_PNCC		0.011		
		(0.06)		
Low_PNSC			-0.436	-0.662
			(-1.23)	(-1.02)
Ab_AP × Low_PNSC			-0.023	
			(-0.89)	
Ab_AP Q5 × Low_PNSC				0.103
				(0.68)
Ab_Temp	0.063*	0.063	0.064*	0.067
	(1.77)	(1.52)	(1.75)	(1.63)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,852	1,852	1,852	1,852
Adj. R^2	-0.002	-0.005	-0.002	-0.004

Panel B: Value-weighted EMC returns, Pollution News Coverage and News Sentiment

	(1) EMC(adj)	(2) EMC(adj)	(3) EMC(adj)	(4) EMC(adj)
Ab_AP	0.048		0.041	
	(1.53)		(1.25)	
Ab_AP Q2		0.431		0.316
		(1.08)		(0.70)
Ab_AP Q3		0.562		0.324
		(1.05)		(0.49)
Ab_AP Q4		0.518		0.174
		(1.03)		(0.29)
Ab_AP Q5		1.225**		0.726
		(2.15)		(1.13)
High_PNCC	-0.333	0.256		
	(-1.34)	(0.44)		
Ab_AP × High_PNCC	-0.014			
	(-0.42)			
Ab_AP Q5 × High_PNCC		-0.170		
		(-0.98)		
Low_PNSC			-0.075	-0.282
			(-0.25)	(-0.45)
Ab_AP × Low_PNSC			0.000	
			(0.02)	
Ab_AP Q5 × Low_PNSC				0.070
				(0.38)
Ab_Temp	-0.024	-0.025	-0.023	-0.023
	(-0.45)	(-0.43)	(-0.41)	(-0.40)
Year × Month FE	Yes	Yes	Yes	Yes
Obs.	1,852	1,852	1,852	1,852
Adj. R^2	0.007	0.005	0.006	0.004

Note: The table presents results from regressions of EMC returns on abnormal air pollution (PM10) variables, controlling for abnormal temperature (Ab_Temp). In Columns 1–2, High_PNCC is a dummy variable that equals one if the month's pollution news coverage, within each country, is high (Pollution News Coverage Change is positive). In Columns 3–4, Low_PNSC is a dummy variable that equals one if the month, within each country, has negative pollution news (Pollution Sentiment Change is below the country's historical monthly median). Equal-weighted portfolio returns are presented in Panel A, while value-weighted returns are presented in Panel B. The sample runs from January 2017 to December 2024, including 22 countries. In all regressions, year-month fixed effects are included and standard errors are clustered by exchange city; the corresponding t-statistics are reported in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels.