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Something in the air: Does air pollution affect fund managers' carbon divestment?

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Something in the Air: Does Air Pollution Affect Fund Managers' Carbon Divestment?*

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Abstract

We examine whether fund managers overestimate carbon risk when they are exposed to local air pollution. We find that air pollution causes managers to underweight stocks of high-emission firms. The effects are stronger for less salient scopes of carbon emissions, among managers located in pro-environmental states, and among those likely to be surprised by air pollution—consistent with the idea that managers revise their beliefs about climate-transition risk following their exposure to air pollution. Carbon-intensive stocks sold by managers who are exposed to air pollution subsequently outperform stocks that they buy, suggesting that such underweighting is costly to fund investors.

JEL classifications: G11, G23, G41, Q5

Keywords: Air Quality Index, Mutual Funds, Carbon Divestment, Salience Bias

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1. Introduction

Institutional investors are under increasing public pressure to divest from carbon-intensive assets. Their role in influencing firms' carbon footprints has sparked one of the most contentious debates in recent years.[1] On the one hand, proponents of divestment argue that fund managers should sell shares of polluting firms because doing so will raise the cost of capital for polluting projects, thereby forcing managers into green-oriented investments where they can, supposedly, obtain cheaper capital.[2] On the other hand, opponents of divestment contend that fund managers should not divest from polluting firms because new shareholders, who are arguably less concerned about climate change than sellers, are less likely to pressure firm managers to undertake green projects.[3] The issue of whether divestment promotes a low-carbon transition notwithstanding, the fact is that many funds still retain significant ownership in polluting firms.[4] It is thus imperative to understand the factors that could affect fund managers' divestment decisions because they are viewed as catalysts that drive firms to reduce their carbon footprints (OECD, 2017; Krueger, Sautner, and Starks, 2020). In this study, we provide new evidence pertaining to the effects of local air pollution on fund managers' behavior regarding the divestment of carbon-intensive assets.

A challenge for fund managers is that climate change is a long-term risk—the adverse impacts of which cannot be measured easily or are not readily observable. While high-

[1] See, for example, the Economist (March 27, 2021). This issue has also divided readers of the Financial Times (FT, March 17, 2021).

[2] Indeed, Royal Dutch Shell acknowledged that the divestment campaign has started to have "a material adverse effect on the price of our securities and our ability to access capital markets." (FT, March 20, 2021)

[3] Berk and Binsbergen (2021) find that divestment has little impact on a firm's cost of capital. Choi, Gao, Jiang, and Zhang (2021) find that divestment influences firms' green policies. There is also evidence that financial institutions may not "walk their talk" (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2021; Heath, Macciocchi, Michaely, Ringgenberg, 2021; Liang, Sun, and Teo, 2021).

[4] For example, Vanguard, BlackRock, Capital Group, and State Street carry the largest holdings of fossil fuel companies as of February 2021 (FT, February 25, 2021).

emission firms have relatively higher climate-transition risk,[5] it is challenging for fund managers to calculate the speed of transition and to justify—above and beyond the expected changes in observable firm fundamentals—the divestment of high-emission firms today. At the same time, investment analyses such as the cash-flow scenarios that are commonly used by fund managers and analysts can be subjective, and accounting for climate-transition risk in these models depends largely on the fund managers' perceptions of the salience of climate risk.[6]

Psychological studies show that decision-makers are subject to salience bias and "local thinking," in which they make judgments in light of what comes to mind when decisions are made (Kahneman and Tversky, 1972; Tversky and Kahneman, 1974; Gennaioli and Shleifer, 2010). It is possible that fund managers do not, on average, incorporate carbon risk adequately in their investment analyses. However, exposure to air pollution in areas where fund managers live and work could affect their local thinking by reminding them of the potential impacts of environmental risks. Indeed, research in psychology and health economics has shown the effects of air quality on cognitive, behavioral, and physical health (Schlenker and Walker, 2016). For example, Jacquemin et al. (2007) ask a large sample of randomly selected adults to rate their annoyance levels following exposure to air pollution and find a high frequency of annoyance caused by air pollution. More seriously, Hall, Brajer, and Lurmann (2008) examine the health impacts of air pollution in California's San Joaquin Valley and find that exceeding federal ozone standards is associated with 460 premature deaths annually. Studies by Schlenker and Walker (2016) and Deryugina, Heutel, Miller, Molior, and Reif (2019) show that air pollution has a causal impact on mortality and heart-related emergency-room admissions in the U.S. Perhaps as a result of these adverse health consequences, individuals who are exposed to air pollution express greater concern about their health and perceived quality

[5] In this paper, we use "carbon risk" and "climate-transition risks" interchangeably, because firms that produce higher carbon emissions likely will be more heavily affected by policies and regulations designed to facilitate the transition to a low-carbon economy.
[6] Capital Group, a $1.9tn Los-Angeles based active manager, conceded that "ESG issues are complex and don't typically lend themselves to simple 'yes or no' decisions on sectors." (FT, February 25, 2021).

of life (Deguen, Ségala, Pédrono, and Mesbah, 2012; Chang, Huang, and Wang, 2018). It is thus plausible that exposure to local air pollution elevates fund managers' concerns about greenhouse gas emissions, which in turn affects their investment analyses and divestment decisions.[7] We call this the salience hypothesis.

We empirically examine the above prediction by studying whether fund managers reduce holdings in firms that produce higher carbon emissions when the air quality in their local areas is poor. We capture a fund manager's exposure to air pollution using the air quality index (*AQI*), which is measured using monitoring stations located within five miles of a fund's headquarters location. Following Bolton and Kacperczyk (2021a, 2021b), we measure a firm's carbon emissions as the natural logarithm of the sum of Scopes 1, 2, and 3 emissions obtained from the S&P Trucost database.[8]

Consistent with the salience hypothesis and local thinking, we find that fund managers reduce holdings in high-emission stocks when the air quality at their locations worsens. The effect is economically meaningful. Following a quarter of low air quality at a fund manager's location, a one-standard-deviation increase in a firm's carbon emissions is associated with a reduction in the stock's portfolio weight that is equivalent to 9.8% of the median dollar value of a stock holding in the fund's portfolio. These results remain robust when we employ alternative carbon emission constructs such as changes in emission levels or industry-adjusted emissions.[9] Moreover, these effects also hold in

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[7] It is also possible that local air pollution causes fund managers to act ethically to save the environment as the *Economist* argues: "*Occasionally*, as with smoking, the moral issues are sufficiently clear-cut for managers to act on unambiguous instructions from their investors [i.e., divestment from carbon firms]. But many issues are more complex and, even in the days of instant cost-free communication, money managers cannot spend their time polling investors and expect to get a useful response. More often, therefore, they should be conservative and set themselves clear aims. That means maximising returns." (Economist, June 27, 2015).

[8] Bolton and Kacperczyk (2021a) find that investors care about carbon emission levels and changes in emission levels, but not emission intensity. Dai, Duan, and Ng (2021) show that it is important to measure a firm's emissions level using all three scope measures as some firms could outsource emissions to supply chain companies.

[9] In Appendix Table A2, we show that our conclusions do not change when we remove the highest-polluting industries from the sample, suggesting that our results are not driven by a handful of prominent polluting industries.

regressions with fund, year-quarter, and location fixed effects, which control for time-invariant fund characteristics and aggregate trends in carbon divestment behavior. Placebo tests using *AQI* values measured in the future or at monitoring stations located farther from a fund's headquarters show an insignificant relationship, suggesting that our findings are not spurious.[10]

While we hypothesize that fund managers reduce the portfolio weights of high-emission firms because they perceive there to be higher climate-transition risks following their exposure to poor air quality, it is possible that air pollution directly and adversely affects firm fundamentals, which then drives fund managers' carbon-divestment actions. Moreover, fund managers who are conscious of environmental risks may choose to locate their offices in areas that feature good air quality, pointing to the endogenous location effect. We implement two identification strategies, which together help us mitigate these concerns. The first strategy is to control for stock × year-quarter fixed effects and fund × stock fixed effects in our regressions. The stock × year-quarter fixed effects control for any unobservable time-varying stock characteristics, thus allowing us to compare, in the same quarter, any change in portfolio weights of a stock made by fund managers who are exposed to air pollution with that of the same stock made by fund managers who are not exposed to air pollution. The inclusion of fund × stock fixed effects ensures that we are not capturing persistent differences across fund managers in their tendency to invest in carbon-intensive assets.

For the second identification strategy, we exploit plausibly exogeneous variations in air pollution caused by strong winds. Prior research shows that sudden strong winds unexpectedly reduce air pollution in a given area (Arain et al., 2007; Deryugina, Heutel, Miller, Molior, and Reif, 2019; Li, Massa, Zhang, and Zhang, 2021), which is plausibly exogenous to fund managers' location choices. We implement a two-stage least squares (2SLS) analysis whereby we instrument local *AQI* with strong winds, defined as those of speeds that are at least two standard deviations above the average wind speed in the

[10] We control for local weather-related variables such as temperature, sunshine, and wind speed in all regressions.

previous year. Our first-stage regressions confirm that strong winds are associated with improved air quality at a fund's location. Using the instrumented *AQI* variables obtained from the first stage, we continue to find a significant effect of exposure to low air quality on fund managers' holdings of high-emission stocks.

In the instrumental variable approach, strong winds should affect only fund managers' holdings of high-emission stocks through the effects of air pollution. While this exclusion restriction assumption is not directly testable, we implement a placebo test by analyzing the effects of strong winds in two subsamples: the first consists of fund managers who are exposed to air pollution, and the other sample contains fund managers who enjoy good air quality at their locations before the strong winds occur. If this criterion is not satisfied, we should observe significant effects of strong winds on fund managers' holdings of high-emission stocks even when air quality is good. We find that the effects of strong winds are insignificant in the subsample of fund managers who have experienced good air quality in their areas. In contrast, when fund managers are exposed to air pollution, we find that strong winds have a positive effect on fund managers' holding of high-emission stocks. This result suggests that by alleviating air pollution, strong winds mitigate fund managers' concern about carbon risk in their portfolios.

We next conduct tests to examine whether the effects of local air pollution are consistent with the salience hypothesis. First, this hypothesis predicts that local air pollution draws fund managers' attention to aspects of carbon emissions that are otherwise less salient on good air quality days. Among the three scopes of carbon emissions, Scope 1 is the most widely reported category. Institutional investors apply exclusionary screens based solely on Scope 1 carbon emissions (Bolton and Kacperczyk, 2021a). In contrast, Scope 2 and in particular Scope 3 carbon emissions are in general less salient. In fact, firms often make commitments to reduce carbon emissions related to Scopes 1 and 2 but are silent on Scope 3 (Dai, Duan, and Ng, 2021). Consistent with the salience hypothesis, we find that the effects of local air pollution on carbon divestment by fund managers are most pronounced with Scope 3 emissions, followed by Scope 2 emissions, but these effects are insignificant for Scope 1 emissions.

Second, if local air pollution causes fund managers to revise their beliefs about climate-transition risk, we expect fund managers who are located in states with pro-environmental attitudes to be more likely to respond to local air pollution. To test this prediction, we sort fund managers into two groups based on whether their headquarters states include a high percentage of survey respondents with pro-environmental attitudes according to the Religious Landscape Survey conducted by the Pew Research Center. We find that the effects of local air pollution are concentrated among fund managers who are located in states with pro-environmental attitudes, whereas these effects are insignificant in other states.[11]

Third, we examine whether the effects of local air pollution on carbon divestment actions by fund managers depend on fund managers' historical exposure to air pollution. As above, we sort fund managers into two groups based on the average *AQI* at their headquarters over the previous year. We find that the effects of local air pollution are more pronounced among funds located in areas where air quality has been good historically, whereas these effects are insignificant when past air quality has been poor. These results are consistent with the idea that fund managers are more likely to be surprised by air pollution if their locations' air quality was good historically.

We then investigate the pricing implications of fund managers' underweighting of high-emission stocks. If the underweighting of these stocks is driven by expected changes in firm performance (e.g., fund managers expect environmental regulations to become more stringent in the near future, harming the performance of high-emission firms), returns on the most underweighted stocks should continue to underperform during the post-exposure period. In contrast, if exposure to local air pollution causes fund managers to overestimate the impact of climate-transition risks on high-emission firms and to sell

[11] In an untabulated analysis, we re-examine the effects of local air pollution on the divestment behavior of socially responsible funds (SRF) and non-SRF based on the average MSCI environmental scores of funds' lagged holdings following the procedure of Cao, Titman, Zhan, and Zhang (2021). We find that our effects are significant for both types of funds. Although the effects on SRF are stronger (the coefficient estimates on $Emissions \times AQI$ are -0.024 for SRF and -0.015 for non-SRF), the difference is not statistically significant. These results are also consistent with our findings for funds that are located in states with pro-environmental attitudes.

such stocks, we expect stock prices to bounce back, that is, abnormal stock returns will be positive during the post-exposure period. Examining the performance of high-emission stocks traded by funds that are exposed to air pollution in the previous year, we find that the most underweighted stocks subsequently outperform those that are most overweighted by exposed funds. Moreover, comparing one-year-ahead gross profitability of and investment by firms in these portfolios, we find that the differences between the most underweighted and the most overweighted portfolios by exposed fund managers are not significant. This result rules out the alternative explanation that the underweighting of high-emission stocks by exposed fund managers is driven by rational expectation of more stringent climate regulations on high-emission firms. Moreover, we do not find these return differentials when we focus on stocks traded by fund managers who are not exposed to air pollution. Taken together, these results lend support to the salience hypothesis.

In the final part of this study, we conduct a number of robustness checks and additional analyses. First, we confirm that our results hold when we replace portfolio weights with the fraction of outstanding shares held by funds or the dollar value of shares traded by funds. This result suggests that the observed underweighting is unlikely to be driven by an overall drop in stock prices of high-emission firms.[12] Second, we examine whether our results are driven by local bias in which fund managers prefer to hold stocks of local firms. We partition the sample into two groups: local firms whose headquarters are located within 100 miles of a fund's headquarters and non-local firms whose headquarters are located outside the 100-mile radius of a fund. Our results remain strong and robust in both subsamples, suggesting that local bias is unlikely to be the explanation. Third, we find that the effects of local air pollution also extend to firms' overall environmental performance. That is, fund managers increase the portfolio weights of firms with high environmental scores when their local air quality conditions worsen. Local air quality, however, does not affect fund managers' portfolio choice based on firms'

[12] We include past individual stock returns in all regressions, which control for the confounding effects of falling stock prices on portfolio weights.

social and governance scores. These results further validate the unique effect of local air pollution on fund managers' concern about environmental-related risks rather than other aspects of a firm's social responsibility or governance quality.

Last, to provide direct evidence supporting the salience hypothesis, we examine analysts' earnings forecasts for high-emission firms. The analyst setting offers the advantage that forecasts more cleanly measure economic agents' beliefs. Based on analyst names and affiliations obtained from IBES, we hand-collect information on their locations by searching their LinkedIn profiles and their affiliated companies' websites. We then follow the same procedure as before to calculate the average *AQI* in the county in which an analyst is located. For identification purposes, we include a stringent set of high-dimensional fixed effects including analyst fixed effects, county fixed effects, stock × year × month fixed effects, analyst × year fixed effects, and/or analyst × stock fixed effects. We find that analysts' earnings forecasts for high-emission firms are more pessimistic after the analysts are exposed to poor air quality in their home counties than forecasts issued for the same firm by analysts who are not exposed to air pollution. Overall, our findings are consistent with the notion that local air pollution affects fund managers' and equity analysts' beliefs about carbon risk and its potential negative impacts on high-emission firms.[13]

Related Literature and Contribution

Our study makes a timely contribution to the current debate over why (or why not) fund managers divest from carbon-intensive firms. Existing studies show that institutional investors' incentives to incorporate climate risks in their portfolio decisions are driven by reputational concerns, social norms, regulatory pressures, or expected

[13] In Appendix Table A5, we replace carbon emissions with firm-level environmental scores obtained from the Sustainalytics database and find that fund managers increase the portfolio weights of firms that achieve good environmental performance after they are exposed to local air pollution. However, when we replace carbon emissions with social and governance scores, we find that the effects of local air pollution are insignificant. These results suggest that local air pollution affects fund managers' beliefs about a firm's environmental risk but not about its social or governance risks.

financial impacts.[14] We show that transitory conditions can also have a significant impact on fund managers' carbon-divestment decisions. While it is beyond the scope of our study to address the issue of whether divestment induces real changes in firms' carbon footprints, our findings shed light on what drives fund managers' divestment decisions: they can be driven by "nudging" factors, specifically local air pollution, rather than persistent preference differences. The portfolio results also suggest that such underweighting of high-emission firms may not benefit fund investors financially.

Our paper contributes to a burgeoning literature documenting that ambient air pollution can lead to biased decision-making and beliefs among financial market participants. Li, Massa, Zhang, and Zhang (2021) use proprietary data on individual investors' trades obtained from a Chinese mutual fund family and find that air pollution exacerbates the disposition bias of these investors. Similarly, Huang, Xu, and Yu (2020) document that individual investors in China make worse trades on days on which air quality is poor. Dong, Fisman, Wang, and Xu (2021) show that air pollution during corporate site visits by analysts lead to more pessimistic earnings forecast. While the above-mentioned studies examine the unconditional effect of air pollution on investors' trading performance and cognitive biases, we focus on the heterogenous effects of air pollution within investors' portfolios. We complement these studies by showing that air pollution also affects economic agents' perceptions of climate-transition risks and hence exert a particularly large impact on the fund managers' perception of high-emission firms.

The climate finance literature has explored the effects of both physical and climate-transition risk on firms (Barrot and Sauviganut, 2016; Dessaint and Matray, 2017; Hsu, Lee, Peng, and Yi, 2018; Choi, Gao, and Jiang, 2020), the stock market (Hong, Li, and Xu, 2019; Alok, Kumar, and Wermers, 2020), the corporate bond market (Huynh and Xia, 2021a, 2021b; Massa and Zhang, 2021), the option market (Ilhan, Sautner, and Vilkov, 2021), bank lending (Brown, Gustafson, and Ivanov, 2021), the real estate market

[14] See, for example, Hartzmark and Sussman (2019), Krueger, Sautner and Starks (2020), Azar, Duro, Kadach, and Ormazabal (2021), Choi, Gao, Jiang, and Zhang (2021), and Gibson, Glossner, Krueger, Matos, and Steffen (2021).

(Bernstein, Gustafson, and Lewis, 2019; Baldauf, Garlappi, and Yannelis, 2020; Duan and Li, 2020; Giglio, Maggiori, Rao, Stroebel, and Weber, 2021), and the municipal bond market (Painter, 2020; Goldsmith-Pinkham, Gustafson, Lewis, and Schwert, 2021). Other studies examine the pricing of environmental regulatory risks in financial markets (de Greiff, Delis, and Ongena, 2018; Hoepner, Oikonomou, Sautner, Starks, and Zhou, 2020; Seltzer, Starks, and Zhu, 2020).[15]

In a closely related study, Bolton and Kacperczyk (2021a) show that investors in the U.S. market require a higher rate of return on stocks of firms that produce higher total carbon emissions and institutional investors do not distinguish between stocks based on Scope 2 or Scope 3 carbon emissions. In particular, Bolton and Kacperczyk (2021a) find that the carbon risk premium rises following the Paris Climate Agreement, which raised investors' overall awareness of climate-transition risk.[16] To facilitate comparison with this result, we examine the effects of local air pollution in two subsample periods, before and after 2015. We find that our results remain strong in both subsamples and the magnitudes are similar in both cases, suggesting that the effects of air pollution on investors' awareness of climate risks are distinct from the effects of the Paris Agreement.

2. Data and Variable Construction

Our sample includes U.S. domestic equity mutual funds' holdings of U.S. public non-financial firms over the 2005-2018 period.[17] We obtain data on actively managed, open-ended U.S. equity mutual funds from the Center for Research in Securities and Prices (CRSP) Mutual Fund database. Mutual funds' quarterly holdings of firms are obtained

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[15] A number of studies examine the pollution risk premium in stock and bond markets (e.g., Chava, 2014; Matsumura, Prakash, and Vera-Munoz, 2014; In, Park, and Monk, 2019; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2019; Duan, Li, and Wen, 2020; Görgen, Jacob, Nerlinger, Riordan, Rohleder, and Wilkens, 2020; Hsu, Li, and Tsou, 2020; Pástor, Stambaugh, and Taylor, 2021a, 2021b).

[16] Sautner, van Lent, Vilkov, and Zhang (2021a, 2021b) develop a firm-level measure of climate change exposure using conference-call data and show that this measure is related to stock returns following the 2015 Paris Agreement.

[17] Our sample starts in 2005, which is the first year of Trucost's carbon emissions data.

from the Thomson Reuters Mutual Fund Holdings (s12) database. We collect air quality data from the EPA's Air Quality System (AQS) database.[18] Firms' carbon emission data come from the S&P Trucost database. We also collect firm-level accounting and market data from the Compustat Fundamentals Annual file and the CRSP. We provide detailed definitions of all key variables in Appendix Table A1.

2.1. *Air Quality Index*

We obtain air quality information from the EPA's Air Quality System (AQS) database. The AQS provides data on air quality indexes for five major air pollutants, i.e., ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and fine particulate matter smaller than 2.5 micrometers in diameter, measured at thousands of monitoring stations located throughout the U.S. We also obtain information on fund headquarters addresses from the CRSP Mutual Fund database and convert them to longitude and latitude coordinates. For each mutual fund, we use the AQI data from all monitoring stations located within a five-mile radius of a fund's headquarters. For each air pollutant, we first obtain the monthly AQI around each fund's location as the maximum daily index over a given month across all monitoring stations located within a five-mile radius of a fund's headquarters.[19] For each fund's location, we then calculate the quarterly AQI for an air pollutant as the average of the monthly AQI over a given quarter. Our analysis uses the quarterly aggregate air quality index (*AQI)*, which is computed for each fund-quarter as the average of the five individual pollutants' quarterly AQIs. For ease of interpretation of the coefficient estimates, we scale the *AQI* by 100.

2.2. *Firms Carbon Emissions Data*

We source firm-level carbon emissions data from the S&P Trucost database. Trucost follows the Greenhouse Gas Protocol and classifies firms' carbon emissions into three

[18] The link to the AQS dataset is: https://aqs.epa.gov/aqsweb/airdata/download_files.html#Daily.
[19] We confirm that our results remain robust when we use the average daily AQI over a given month.

categories. Scope 1 emissions are directly generated by burning fossil fuels and production processes owned or controlled by a firm. Scope 2 covers indirect emissions produced by a firm's consumption of purchased electricity, heat, or steam. Scope 3 emissions, which are estimated using an input-output model, include indirect emissions produced by the extraction and production of purchased materials and fuels, electricity-related activities not covered in Scope 2, outsourced activities, waste disposal, etc. Trucost provides firm-level annual carbon emissions, measured in tons, for each category. We follow Bolton and Kacperczyk (2021a) to construct firm-level total carbon emissions (*Emissions*) as the natural logarithm of the sum of the emissions in all three categories. We also confirm that our results are robust to using alternative measures of carbon emissions such as industry-adjusted carbon emissions and changes in the carbon emissions level.

2.3. *Mutual Funds' Portfolio Weights and Fund Controls*

Our data on mutual funds lie at the intersection of the CRSP Mutual Funds database and mutual funds' quarterly holdings from the Thomson Reuters Mutual Fund Holdings (s12) database. Following prior research, we focus on diversified domestic actively managed equity mutual funds and remove index funds using CRSP-defined style indicators and fund names—thus, we require a fund name to be non-missing. In addition, we mitigate the impact of small funds on our analysis by eliminating funds with a total net assets (TNA) of less than $10 million or that hold fewer than 10 stocks (Elton, Gruber, and Blake, 2001). We also remove the first 18 months of data for each fund to reduce the effect of incubator bias (Evans, 2010). Last, following Kacperczyk, Sialm, and Zheng (2008), we exclude funds whose equity holdings are on average less than 80% of TNA.

For each quarter, we calculate the weight of a stock in a mutual fund's portfolio (*Weight*) as the dollar holdings of the stock scaled by the total dollar holdings of all stocks in the mutual fund's portfolio.[20] As most funds have multiple share classes – they

[20] In our main analyses, we use portfolio weight as the measure of investor demand, following Koijen and Yogo (2019). Robustness tests show that our main findings still hold when we use alternative

typically differ only in the fee structure and the target clientele but have the same holdings – we aggregate these classes into a single fund. In particular, we compute fund size, *Ln(Fund Size)*, as the natural logarithm of the sum of total net assets (*TNA*) of its share classes. A fund's quarterly returns, *Fund Ret*, is the weighted average of returns over the share classes, using individual share classes' TNA as the weight. Similarly, we also control for the fund-level weighted average expense ratio (*Exp Ratio*) and the turnover ratio (*Turn Ratio*), using individual share classes' TNA as the weight. In addition, we include fund flows over quarter *t*, *Fund Flow*, which is measured as $[TNA_t - (1 + Fund\ Ret_t)TNA_{t-1}]/TNA_{t-1}$.

2.4. *Firm Controls*

We also control for a set of firm-level characteristics that could determine fund holdings. Firm size, *Size*, is measured as the natural logarithm of a firm's market capitalization, where market capitalization is calculated as stock price multiplied by the number of shares outstanding. *Ln(BM)* is computed as the natural logarithm of one plus the book-to-market ratio, where the book-to-market ratio is the book value of equity divided by market capitalization. *Momentum* represents continuously compounded returns on a stock over the previous year. In addition, we control for *Return on Assets*, measured as operating income before depreciation divided by total assets. *Sales growth* is the difference between firm-level sales in the current year and sales in the previous year scaled by sales in the previous year. Last, we include *Leverage* measured as the sum of long-term debt and debt in current liabilities divided by the market value of assets, where the market value of assets is computed as total assets minus the book value of equity plus market capitalization.

2.5. *Weather-Related Controls*

measures of investor demand including dollar value of a stock traded by the fund and change in percentage shares of a stock held by the fund.

To account for the possibility that the *AQI* is related to weather conditions, we control for weather-related variables. We collect weather information from the National Climatic Data Center (NCDC). The NCDC reports the daily sunshine times, wind speeds, and temperatures provided by monitoring stations across the U.S. We calculate sunshine time, *TSun*, as the natural logarithm of one plus the average daily sunshine time (in minutes) over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location. We control for wind speed, *Wind*, measured as the natural logarithm of one plus the daily average wind speed (in tenths of meters per second) over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location. We also include temperature, *Tmp*, calculated as the average daily temperature over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location.[21] As per the convention in the NCDC database and the climatology literature, in our analysis we measure temperatures in degrees Celsius. Following the prior literature (Deryugina and Hsiang, 2014), we compute the daily average temperature as the average of the maximum temperature and the minimum temperature within a given day.

2.6. *Sample and Summary Statistics*

After selecting data from the intersection of various sources and applying the aforementioned filters to fund characteristics, the final sample comprises 2,479,757 fund-stock-quarter observations for the period spanning 2005 through 2018. In Table 1, we report the summary statistics for the key variables used in the baseline analysis. On average, the weight of a stock in a mutual fund's portfolio is 0.759%. *AQI*, which is scaled by 100, has a mean of 0.461 and a standard deviation of 0.147. The average *Emissions* value is 13.84, which is equivalent to 1.02 tons of carbon emissions under all three scopes. An

[21] We omit observations where the maximum temperature exceeds 60°C (140°F) or the minimum temperature is lower than -80°C (-112°F) as they are likely errors (Deryugina and Hsiang, 2014). We also remove weather station-years for which we can observe fewer than 200 daily weather temperatures in a given year (Auffhammer, Hsiang, Schlenker, and Sobel, 2013; Deryugina and Hsiang, 2014).

average fund in our sample holds $395.05 million and sustains an expense ratio of 0.01, a turnover ratio of 0.79, a fund flow of -0.003, a *TSun* value (the natural logarithm of sunshine time) of 3.60, a *Wind* value (the natural logarithm of wind speed) of 3.53, and an average temperature of 9.83°C. The average monthly fund return over a quarter is about 0.50%. A typical firm in our sample has market capitalization of $9.78 billion, *Ln(BM)* of 0.35, stock momentum of 15.10%, a *Return on Assets* ratio of 0.14, a sales growth rate of 8.90%, and a *Leverage* ratio of 0.15.

[Insert Table 1 About Here]

Figure 1 Panel A presents the distribution of fund locations across the U.S. states. It shows that while funds are scattered throughout the U.S., the top 10 states that host the most mutual funds are, in descending order, New York, Massachusetts, California, Illinois, Ohio, Connecticut, Texas, Pennsylvania, Maryland, and Minnesota. Panel B displays the number of fund-quarters in which local air quality is not considered ideal for human health (i.e., *AQI* is above 50, representing moderately poor or hazardous air). Funds that are most severely exposed to sub-par air quality are located in New York, Illinois, Massachusetts, Maryland, Missouri, California, Ohio, Pennsylvania, Connecticut, and Wisconsin (in descending order).[22,23]

[Insert Figure 1 About Here]

3. Empirical Analysis

[22] Note that our analysis exploits exogenous variations in local *AQI*. We also control for fund × stock fixed effects and fund county × year-quarter fixed effects, suggesting that the effects of *AQI* cannot be fully explained by static differences between funds located in financial centers and funds located in other places. In an untabulated analysis, we find that our results remain robust when we remove funds located in these Top 10 states from the sample. These analyses also address the concern that the locations of air monitoring stations are correlated with the locations of fund managers.

[23] Another related concern is that some air monitoring stations are shut down in certain quarters and these events may be correlated with the divestment behaviour of fund managers. In our sample, there are 12.67% fund-quarters that have missing AQI information. To examine this concern, in an untabulated analysis, we estimate our baseline regression using a sample of funds that do not have missing AQI in any quarter during their fund lives. Our results continue to hold.

We begin our analysis by examining whether the portfolio weights of stocks by high-emission firms depend on the air quality in fund managers' local areas. We then discuss potential endogeneity issues arising from omitted variable bias and fund managers' location choices. Next, we report findings from additional analyses that together lend support to the salience hypothesis, and finally we conduct a number of robustness checks.

3.1. Portfolio Weights of Carbon Emitting Firms and Fund Managers' Exposure to Local Air Pollution

This study's primary hypothesis is that poor air quality in the area where a fund manager is located elevates her concern about carbon risk, which in turn causes her to reduce holdings of stocks of carbon-intensive firms. To test this prediction, we estimate the following model:

$$Weight_{f,i,t+1} = \beta_0 + \beta_1 Emissions_{i,t} \times AQI_{f,t} + \beta_2 AQI_{f,t} + \beta_3 Emissions_{i,t} + \delta' X_{f,t} + \gamma' S_{i,t} + \varphi_f + \mu_i + \theta + \tau_t + \varepsilon_{f,i,t} \qquad (1)$$

where $Weight_{f,i,t+1}$ is the weight of stock i in a mutual fund f's portfolio at the end of quarter t+1, where the weight is calculated as the dollar holdings of a stock divided by the total dollar holdings of all stocks in the mutual fund's portfolio.[24] $Emissions_{i,t}$ is the natural logarithm of firm i's total carbon emissions. $AQI_{f,t}$ is the average aggregate AQI across all monitoring stations located within five-mile radius of mutual fund f's location over quarter t. A higher index indicates lower air quality and, in particular, an index with a value greater than 100 represents air pollution. $X_{f,t}$ and $S_{i,t}$ represent sets of fund-level control variables and stock-level control variables, respectively. φ_f, μ_i, θ, and τ_t indicate fund, stock, fund's county, and year-quarter fixed effects. Our salience hypothesis predicts that the coefficient β_1 is negative. The null hypothesis is that β_1 is insignificantly different from zero if local air pollution does not affect fund managers' perception about

[24] If fund f holds a positive weight in stock i in quarter t and then liquidates its position in stock i completely in quarter t+1 (i.e., $Weight_{f,i,t}$ is positive and $Weight_{f,i,t+1}$ is missing), we set $Weight_{f,i,t+1}$ to zero.

climate risks. This could be the case because ambient air pollution is largely driven by idiosyncratic factors (such as local weather) that is not informative about expected climate policies and fund managers are relatively sophisticated investors.

Table 2 Panel A presents the estimation results for regression (1). In Column 1, we present the results for the regression without control variables. The regression associated with Column 2 incorporates control variables that include local weather variables (sunshine, temperature, and wind speed), fund-level characteristics, and stock-level characteristics. Column 3 displays the results of the same regression as Column 2 but additionally includes the interaction terms between *Emissions* and weather variables. All regressions control for fund, firm, fund county, and year-quarter fixed effects. Standard errors are clustered at the fund and year-quarter levels.[25]

[Insert Table 2 About Here]

Across all models, the coefficients on *Emissions* × *AQI* are negative and statistically significant at the 1% level—that is, a fund manager reduces portfolio weights of stocks of high-emission firms when the *AQI* at the fund manager's location is higher (i.e., the air quality is lower). Although we make no predictions regarding the coefficient on *AQI*, it is positive, indicating that funds that are exposed to lower air quality tend to have larger portfolios weights.[26] (This coefficient is, however, insignificant when we control for county × year-quarter fixed effects for Table 3.) The coefficient estimate on *Emissions* is positive and statistically significant, which is consistent with the view that funds generally maintain large holdings in high-emission firms.

The results reported in Column 2 show that the coefficient on *Emissions* × *AQI* remains negative and statistically significant at the 1% level even with the control variables included. In Column 3, the coefficient on *Emissions* × *Tsun* is positive while the coefficient on *Emissions* × *Tmp* is negative, suggesting that the portfolio weights of high-emission stocks are higher (lower) when fund managers are exposed to longer periods of

[25] Our results are robust to standard errors clustered at the fund, firm, and year-quarter levels.
[26] Given that *AQI* is measured at the fund-quarter level, it is likely that the positive coefficient on *AQI* reflects the fact that funds exposed to high *AQI* maintain smaller total portfolio holdings.

sunshine (higher temperatures). The coefficient on *Emissions* × *Wind* is insignificant, indicating that fund managers' holdings of carbon-emitting stocks are not sensitive to local wind speed. These results might be consistent with the idea that fund managers are more (less) optimistic about the prospects of high-emission firms when they are exposed to longer periods of sunshine (warmer temperatures).[27] Our coefficient of interest, *Emissions* × *AQI*, remains negative and statistically significant at the 1% level, suggesting that the effects of air quality are distinct from the effects of weather.

We next examine the nonlinear effects of *AQI* on mutual funds' portfolio weights of high-emission stocks. Specifically, we replace *AQI* in regression (1) with one of the three dummy variables that indicate the level of air quality: *Low AQI* equals 1 if the *AQI* is below 50 (healthy air conditions) and zero otherwise; *Med AQI* equals 1 if the *AQI* is between 50 and 100 (moderate air conditions) and zero otherwise; and *High AQI* equals 1 if the *AQI* is above 100 (polluted and unhealthy air conditions) and zero otherwise.

In Table 2 Panel B, we report the estimation results. We indeed observe significant nonlinear effects of *AQI* on the portfolio weights of carbon-intensive stocks. Specifically, the coefficient on *Emissions* × *Low AQI* is 0.003, which is significant at the 5% level and indicates that fund managers increase the weights of high-emission firms when they enjoy good air quality in their areas. However, these effects reverse as local air quality worsens. Specifically, the coefficient estimates on *Emissions* × *Med AQI* and *Emissions* × *High AQI* are, respectively, −0.002, which is significant at the 10% level, and -0.018, which is significant at the 1% level. The effects of air pollution are also economically meaningful. For example, the coefficient estimate on *Emissions* × *High AQI* (*Emissions* × *Low AQI*) indicates that, after a fund manager is exposed to poor (good) air quality, an increase in *Emissions* by one standard deviation is associated with a reduction (an increase) in the

[27] Hirshleifer and Shumway (2003) document a positive relationship between sunny days (which are associated with investors' upbeat moods) and stock returns. Duan and Li (2020) find that mortgage lenders are more concerned about climate change on warmer days. Shao, Garand, Keim, and Hamilton (2016) analyze the 2009 Pew General Public Science Survey and find that public perceptions of climate change depend on long-term summer temperature trends in their home communities.

portfolio weight in a given stock by −0.04% (0.006%), which is equivalent to a 9.8% drop (1.5% increase) in the dollar value of each stock in the portfolio.[28]

To establish robustness, we repeat our baseline regressions by employing two alternative measures of carbon emissions. The first alternative measure is industry-adjusted carbon emissions (*Emissions Adj*), which is calculated as the difference between firm-level *Emissions* and the industry average of *Emissions* based on the Fama and French 48 Industry Classification. We report the results in Appendix Table A2 Panel A. Our results remain robust when using the industry-adjusted carbon emissions measure.[29] We also follow Bolton and Kacperczyk (2021a) in constructing a second alternative measure, $\Delta Emissions_t$, which is computed as the difference between $Emissions_t$ and $Emissions_{t-1}$, divided by $Emissions_{t-1}$. We present the results In Appendix Table A3. The coefficient on *ΔEmissions* × *AQI* is negative and significant at the 1% level, suggesting that, when the air quality at fund managers' locations is poor, they reduce the portfolio weights of stocks of firms that produce large increases in carbon emissions.

3.2. *Endogeneity*

In this section, we provide evidence pertaining to the causal effects of local air pollution on the portfolio weights of stocks of carbon emitting firms. We first employ high-dimensional fixed effects to control for unobservable factors. We then perform an instrumental variable analysis, in which we use strong local winds as an exogenous source of variation in local air pollution.

3.2.1. *High-Dimensional Fixed Effects*

[28] We compute −0.04% as -0.018×2.038, where 2.038 is the standard deviation of *Emissions*. We compute 9.8% as $\frac{-0.04 \times \$406{,}099{,}986}{\$1{,}651{,}787}$, where \$406,099,986 is the median size of a mutual fund portfolio in our sample, and \$1,651,787 is the dollar value invested in the median stock (unreported). Similarly, we calculate 0.006% and 1.5% using the corresponding coefficient estimate on *Emissions* × *Low AQI*.

[29] In Appendix Table A2 Panel B, we further show that our baseline findings remain robust when we remove top polluting industries from the sample. These results suggest that our results are not driven by the top polluting industries.

An important source of omitted variable bias is that carbon-polluting firms that are underweighted by fund managers who are exposed to air pollution differ with respect to key characteristics from other firms in their portfolios and these characteristics may not be fully accounted for in our regression model. Fortunately, we can control for these unobservable differences by including a full set of fund × stock fixed effects and stock × year-quarter fixed effects.[30] The inclusion of fund × stock fixed effects ensures that the effects of local air pollution are identified after accounting for fund managers' persistent preference differences regarding carbon-intensive firms (Hong and Kostovetsky, 2012). The inclusion of stock × year-quarter fixed effects ensures that our results are not driven by unobserved (even time-varying) firm characteristics that may correlate with firms' carbon emissions. We also include fund county × year-quarter fixed effects to control for local economic conditions at the county level that may correlate with *AQI* and affect fund managers' portfolio decision.

In Table 3, we report the estimation results for regression (1) but control for fund × stock, county, and year-quarter fixed effects for Column 1, fund × stock, stock × year-quarter, and county fixed effects for Column 2, and county × year-quarter, fund, and stock fixed effects for Column 3. The results show that the coefficient on *Emissions* × *AQI* remains negative and statistically significant at the 1% level. For Columns 4, 5, and 6, we further control for interactions between *Emissions* and each of the weather variables. We find that the interaction terms with local sunshine and with local wind speed become insignificant. Although the coefficient on the interaction term between *Emissions* and temperature is negative and significant in the regression with fund × stock fixed effects, it is significant only at the 10% level when we include stock × year-quarter fixed effects in the regression. Even in these regressions that control for the effects of weather variables, we continue to find a negative and significant coefficient on *Emissions* × *AQI*.

[Insert Table 3 About Here]

[30] In Section 3.3.5, we present a portfolio analysis that also rules out this alternative explanation.

3.2.2. Strong Winds as an Instrument for Air Quality

We use an identification strategy proposed in prior research (e.g., Deryugina, Heutel, Miller, Molior, and Reif, 2019; Li, Massa, Zhang, and Zhang, 2021) that uses strong winds as a source of exogenous variation in air quality at a fund manager's location. Specifically, for each fund manager's location, a strong wind occurs when the average wind speed over a quarter is more than two standard deviations above the average wind speed in the area over the previous year. We then estimate the following two-stage least squares (2SLS) regressions:

First-stage regressions:

$$AQI_{f,t} = a_0 + a_1 StrongWind_{f,t} + a_2 Emissions_{i,t} \times StrongWind_{f,t} + a_3 Emissions + \delta' X_{f,t} + \gamma' S_{i,t} + \varphi_f + \mu_i + \tau_t + \epsilon_{p,t}, \quad (2)$$

$$Emissions_{f,t} \times AQI_{f,t} = a_0 + a_1 StrongWind_{f,t} + a_2 Emissions_{f,t} \times StrongWind_{f,t} + a_3 Emissions + \delta' X_{f,t} + \gamma' S_{i,t} + \varphi_f + \mu_i + \tau_t + u_{p,t}, \quad (3)$$

Second-stage regression:

$$Weight_{f,i,t+1} = b_0 + b_1 \widehat{AQI_{f,t}} + b_2 \widehat{Emissions_{i,t}} \times AQI_{f,t} + b_3 Emissions_{i,t} + \delta' X_{f,t} + \gamma' S_{i,t} + \varphi_f + \mu_i + \tau_t + \varepsilon_{f,i,t}, \quad (4)$$

where $StrongWind_{f,t}$ is a dummy variable that is equal to one if a strong wind occurs at a fund manager *f*'s location in quarter *t* and zero otherwise. $\widehat{AQI_{f,t}}$ and $\widehat{Emissions_{i,t}} \times AQI_{f,t}$ are the predicted values obtained from the first-stage regressions. Other variables are defined as in equation (1).

In Table 4 Panel A, we report the estimation results. In Columns 1 and 2, we report the first-stage regression results, while Column 3 displays the estimation results for the second stage. The coefficient on *StrongWind* is negative and statistically significant at the 1% level. Consistent with our expectations, these results suggest that strong winds cause *AQI* to be lower (i.e., air quality conditions are healthier) and that *Emissions* × *StrongWind* is a reasonable instrument for *Emissions* × *AQI*. The results reported in Column 3 show that higher instrumented *AQI* leads to lower weights of high-emission stocks in fund portfolios. The Cragg-Donald Wald *F*-statistic for the weak identification test is 36.56, which is statistically significant. This suggests that *StrongWind* is unlikely to be a weak instrument for the *AQI*.

[Insert Table 4 About Here]

It is possible that strong winds have direct effects on the portfolio weights of high emission firms, creating bias in our 2SLS analysis. We examine whether this is the case by conducting a subsample analysis. Specifically, we partition our sample into two groups based on whether the air quality index in the previous quarter at a fund's location is above or below 100. We then estimate regression (1) but replace *AQI* with *StrongWind* for each subsample and report the results in Table 4 Panel B. In the subsample of *AQI*<100, the coefficient on *Emissions* × *StrongWind* is -0.003 with an associated *t*-statistic of -0.947, which is statistically insignificant even at the 10% level. In contrast, the results for the subsample of *AQI*≥100 show that the coefficient on *Emissions* × *StrongWind* is 0.011 (*t*-statistic = 2.65), which is statistically significant at the 1% level. These results suggest that strong winds affect the portfolio weights of carbon emitting firms only when fund managers are exposed to air pollution (i.e., when strong winds can dissipate air pollution) but not when air quality conditions are good in the first place. It is thus unlikely that our 2SLS analysis is biased by the direct effects of strong winds.

3.2.3. Placebo Analyses

In the previous section, we show that fund managers reduce holdings in stocks of firms with higher carbon emissions when the air quality conditions within five miles of their locations are poor. In this section, we conduct two placebo analyses to show that our results are not spurious.

In the first test, we consider the effects of *AQI* measured at remote locations relative to a given fund manager. Specifically, using the same method to calculate average *AQI* as we used above, we construct three additional *AQI* measures, *AQI[6, 100]*, *AQI(100, 200]*, *AQI(>200)*, which respectively capture the air quality index averaged across air quality monitoring stations located between 6 miles and 100 miles, between 100 miles and 200 miles, and more than 200 miles from a fund headquarters' location. We expect these distant *AQI* measures to exert insignificant effects on the portfolio weights of carbon emitting firms.

We estimate regression (1) but additionally control for these distant *AQI* measures and their interactions with *Emissions.* The results reported in Table 5 Panel A show that none of these distant *AQI* measures has a significant effect, while the effects of local *AQI* (measured within five miles of a fund manager's location) remain strong.

[Insert Table 5 About Here]

For the second placebo analysis, we examine the effects of future *AQI* on funds' portfolio weights. To the extent that *AQI* is not perfectly predictable, we expect that future *AQI* will not affect current portfolio weights.[31] We construct two future *AQI* measures, *AQI_Nxt1yr* and *AQI_Nxt2yr*, which measure the *AQI* of the same quarter but in the following one and two years, respectively. We repeat regression (1) but add one of the future *AQI* measures and its interaction with *Emissions.* We report the results in Table 5 Panel B. The coefficients on *Emissions* × *AQI_Nxt1yr* and *Emissions* × *AQI_Nxt2yr* are insignificant, while *Emissions* × *AQI* remains significant. These placebo results indicate that our findings are unlikely to be driven by spurious factors.

3.3. *Channel and Related Tests*

In this section, we present a battery of tests that point toward the interpretation that fund managers become more concerned about climate-transition risk following their exposure to poor air quality conditions. We design our tests based on the implications of the salience hypothesis, as we do not directly observe fund managers' beliefs.

3.3.1. *Local Air Pollution and Attention to Less Salient Emissions Scopes*

[31] We examine the autocorrelation of *AQI* by regressing *AQI* in the current quarter on *AQI*s measured in the previous seven quarters and find that the coefficients on the previous quarters' *AQI*s are positive and significant for up to four lags only.

A firm's emissions can be classified into three scopes: Scope 1 measures direct emissions generated by production. Scope 2 captures indirect emissions from consumption of purchased electricity, heat, or steam, while Scope 3 reflects other indirect emissions incurred upstream and downstream along the supply chain. Whereas Scope 1 emissions are widely reported and used in exclusionary screenings by institutional investors, Scopes 2 and 3 are generally less salient (Bolton and Kacperczyk, 2021a). We can therefore take advantage of the relative salience of these emission scopes to examine the salience hypothesis. If local air pollution raises fund managers' awareness of carbon risk, we expect the effects to be stronger for Scope 2 and most pronounced for Scope 3 carbon emissions.

To obtain the results reported in Table 6, we estimate regression (1) but replaces *Emissions* with the natural logarithm of individual scopes of carbon emissions. We find that the coefficient on *Emissions* × *AQI* in the regression for Scope 3 emissions is twice as large in magnitude as that in the regression for Scope 2 emissions, while this coefficient is insignificant in the regression for Scope 1 emissions. These results are consistent with the notion that exposure to air pollution heightens fund managers' concerns about less salient scopes of carbon emissions, to which they normally pay less attention.

[Insert Table 6 About Here]

3.3.2. Pro-Environmental Attitude, Portfolio Weights, and Air Quality

The American public is divided over both the reality of global warming and whether stringent climate regulations, which will more severely affect carbon-intensive firms, are warranted. In a 2014 survey by the Pew Research Center, only 57% of respondents agreed that stricter environmental laws and regulations are worth the price. To the extent that fund managers share their local public views about climate change, we expect the effects of local air pollution to depend on states' attitudes toward climate risk.

We proxy for a fund manager's belief about climate-transition risk using public views of strict environmental regulations in her headquarters state, which we obtain from the 2014 Religious Landscape Survey conducted by the Pew Research Center. This survey is based on telephone interviews with more than 35,000 Americans from 50 U.S. states. We use state-level summary statistics that show the number of respondents who agreed that stricter environmental laws and regulations are worth the price and measure the proportion of supporters. We partition states into two groups based on the sample median of this measure, where the high group contains states with above-median proportion of respondents who support environmental regulations and the low group consisting of all other states. Accordingly, we assume that a fund manager who is located in a pro-environmental state is also more likely to adopt a pro-environmental attitude.[32]

We re-estimate our baseline regression using each subsample and report the results in Table 7. Columns 1 and 2 present the estimation results for the subsamples that are split based on the number of survey participants who support stricter environmental laws scaled by the total number of survey participants (including supporters, opponents, and those with a neutral view) in a given state. Columns 3 and 4 display the results for the subsamples that are partitioned based on the number of supporters of stricter environmental regulations scaled by the sum of supporters and opponents of stricter environmental regulations. For both measures, we find that the effects of local air pollution are negative and significant among fund managers who are located in pro-environmental states, while these effects are insignificant for fund managers who are located in states where the percentage of pro-environmental respondents is low. These results are consistent with the notion that fund managers who are located in pro-environmental states are likely to be more are willing to take actions (and pay a price) to contribute to transition to a low-carbon economy.

[Insert Table 7 About Here]

In Appendix Table A4, we use a state's political orientation as an alternative proxy for the state's attitude toward climate change. This proxy is motivated by prior research showing that Republicans and conservatives are more likely to be skeptical about man-made global warming than Democrats and liberals (Pew Research Center, 2006, 2007;

[32] Managers who exhibit pro-environmental attitudes may choose to be located in pro-environmental states. As we argue and show in Section 3.2, to the extent that changes in air quality conditions are exogenous, the location choice is unlikely to bias our results.

Gallup, 2008; Hong and Kostovetsky, 2012; Shao, Keim, Garand, and Hamilton, 2014). We thus conjecture that fund managers located in Democratic states are more likely to be concerned about climate risk than those located in Republican states. We classify a state as "Democratic" or "Republican" if the state governor's party is Democratic or Republican. We continue to find that the effects of local air pollution are concentrated among Democratic states.

3.3.3. Historical Exposure to Air Pollution and Portfolio Weights

Our next analysis examines whether fund managers respond more strongly to local air pollution when they have been exposed to good air quality in the past. Managers who are not accustomed to poor air quality conditions should react more strongly psychologically to air pollution than managers who have experienced poor air quality in the past (Busse, Pope, Pope, and Silva-Risso, 2015). To test this prediction, for each fund we compute the historical average of the *AQI* at its headquarters location over the previous year.[33] We then partition fund managers into two groups based on their previous year's average *AQI*, where the good air quality group contains funds whose historical average *AQI* is below 100 and the poor air quality group consists of funds whose historical average *AQI* is above or equal to 100.

We report the estimation results in Table 8. Consistent with our prediction, we find that, in a given quarter, the effects of local air pollution on the portfolio weights of high-emission stocks are more pronounced in the subsample of funds that are headquartered in localities with good air quality in the previous year. In contrast, regarding funds that have been exposed to air pollution previously, these effects are not significant. These results are consistent with the notion that fund managers are more likely to be shocked by air pollution, and hence are more likely to update their beliefs about climate-transition risk, when they have enjoyed good air quality in the past. The insignificant results for

[33] In an untabulated analysis, we estimate the regression of *AQI* on its lagged values, controlling for fund fixed effects and county × year fixed effects. We find that the autocorrelation of *AQI* is positive and significant up to four quarters only.

managers who are exposed to poor air quality historically also suggest that local air pollution is no longer salient for these managers and hence has no effects on their perception of carbon risk.

[Insert Table 8 About Here]

3.3.4. Long-Run Portfolio Response

Another prediction generated by the salience hypothesis is that, as an individual's memories of air pollution fade over time, the effects of local air pollution on fund managers will gradually diminish. To examine this prediction, we re-estimate regression (1) but replace the dependent variable with portfolio weights measured during the period running from two quarters to four quarters into the future.

In Table 9, we report the estimation results. We find that the effects of air pollution diminish with time. For example, in Column 1 for which the dependent variable is two-quarters-ahead portfolio weights, the coefficient on the interaction term $Emission \times AQI$ is -0.013 with an associated t-statistic of -3.584, which is significant at the 1% level. This coefficient remains negative and significant at the 5% level in the regression of three-quarters-ahead portfolio weights, but the magnitude is smaller. The effect becomes insignificant in the regression of four-quarters-ahead portfolio weights. Again, these results are consistent with this memory-related implication of the salience hypothesis.

[Insert Table 9 About Here]

3.3.5. Impacts on Stock Returns

If local air pollution affects fund managers' perceptions of carbon risk, we expect them to overreact by selling high-emission stocks (Gennaioli and Shleifer, 2010; Alok, Kumar, and Wermers, 2020). Such overreactions will then revert, causing stocks that are underweighted by fund managers who are exposed to air pollution to generate positive abnormal returns subsequently. On the other hand, if the underweighting of carbon-emitting firms is justified by the expected changes in firm fundamentals (e.g., these high-emission firms can be more severely affected by stringent climate regulations), then we should not observe significant return reversals. To test this implication, we follow Alok, Kumar, and Wermers's (2020) approach by comparing the performance of underweighted stocks with that of stocks that are overweighted by these exposed fund managers.

Specifically, for each year in the sample period, we first identify top polluting firms by sorting firms into quintiles based on their total carbon emissions as measured in the previous year, where firms in the top quintile with high *Emissions* values are considered Top Polluters. Independently, for each quarter, a fund is deemed to be exposed to poor air quality if the AQI at the fund's locality measured in quarter $t-1$ is at least one standard deviation above its prior year's average (hereafter referred to as Exposed Funds); all other funds are considered Unexposed Funds.[34] We then compute the change in weights of stocks of Top Polluters in the Exposed and Unexposed Funds' portfolios as $Ln\left(Weight_{f,i,t}\right) - Ln(Weight_{f,i,t-2})$. For each Top Polluter's stock, we compute the average change in weights across Exposed and Unexposed Funds.

We then sort stocks into quintiles based on the average change in stock weights by Exposed Funds, where quintile 1 contains Top Polluters' stocks that experience the lowest average change in weight (the most underweighted) and quintile 5 contains Top Polluters' stocks that experience the highest average change in weight by Exposed Funds (the most overweighted). We evaluate the abnormal returns over holding horizons of 1 year to 3 years. As a benchmark, we also consider the abnormal returns on portfolios sorted on the change in stock weights by Unexposed Funds. We report *t*-statistics computed using Newey-West standard errors with 5 lags.

In Table 10, we report value-weighted portfolio returns that are adjusted for Fama and French's (2015) five risk factors and the momentum factor. Panel A presents the

[34] We confirm that our results remain robust when (i) we define Exposed Funds as those where the local AQI is above 100, or (ii) we define Exposed Funds by sorting mutual funds into quintiles based on the average AQI at their locations over the previous year, where quintile 1 contains funds with low AQI values (Unexposed Funds) and quintile 5 contains funds with high AQI values (Exposed Funds).

abnormal returns on the quintile portfolios constructed based on changes in weights by Exposed Funds, while Panel B displays the abnormal returns on portfolios constructed based on changes in weights by Unexposed Funds. In Panel C, we report the differences in returns between these two sets of portfolios of Exposed Funds and Unexposed Funds.

[Insert Table 10 About Here]

Regarding the results reported in Panel A, we observe that stocks that are underweighted by Exposed Funds outperform stocks that are overweighted by these funds during the period running from 1 to 3 years after portfolio formation, suggesting that strong return reversals in the portfolios of Exposed Funds occur. These return reversals do not, however, occur in the portfolios of Unexposed Funds (Panel B). For example, during the 1-year period following portfolio formation, the abnormal return on underweighted-minus-overweighted portfolios of Exposed Funds is 36.6 bps per month or 439 bps per year, which is economically meaningful and statistically significant at the 5% level. In contrast, the abnormal return spread for the portfolios of Unexposed Funds is only 4.4 bps per month or 53 bps per year, which is economically small and statistically insignificant.

In Panel C, we report the differences in returns between the portfolios of Exposed Funds and those of Unexposed Funds. We find that, during the portfolio-formation period, the difference between the two portfolios is insignificant. However, during the holding period that runs from 1 year to 3 years, portfolios of Exposed Funds exhibit stronger return reversals than those of Unexposed Funds and the differences are significant.

The significant return reversals on underweighted-minus-overweighted portfolios of Exposed Funds suggest that exposed fund managers' carbon divestment actions are not warranted by expected changes in carbon-emitting firms' future fundamental performance. As another test of fund managers' overreaction to local air pollution, we examine differences in firm fundamentals between the most underweighted and most overweighted stocks by Exposed Funds. Using operating profitability and investment as measures of firm fundamentals (as defined in Fama and French (2015)), Panel D shows that the differences in these measures between underweighted stocks and overweighted stocks by Exposed Funds are not statistically different from zero during either the formation period or the holding period. In sum, both the stock returns and the fundamental performance analysis suggest that the underweighting of high emission stocks by exposed fund managers likely reflects their overreaction to climate-transition risk after experiencing local air pollution.

3.4. *Sensitivity Checks and Additional Analyses*

3.4.1. *Alternative Measures of Portfolio Response*

A potential concern regarding our baseline tests is that the drop in portfolio weights of carbon emitting firms may be driven by the falling stock prices of those firms, even if the funds do not sell stocks of carbon emitting firms. To address this concern, we repeat our baseline regression but use alternative measures of fund portfolio responses as the dependent variable. The first alternative measure, $Shares\ Pct_{t+1}$, is the ratio of the total number of shares of a stock held by a mutual fund in quarter t+1 to the total number of shares outstanding. The second alternative measure, $Traded\ Value_{t+1}$, is the dollar value of the shares of a stock traded (either bought or sold) by a mutual fund during quarter t+1. We report the results in Table 11.

[Insert Table 11 About Here]

In Column 1 of Table 11, we present the results for the regression with $Shares\ Pct_{t+1}$ as the dependent variable. The regression results reported in Column 2 use $Traded\ Value_{t+1}$ as the dependent variable. We find that, in both specifications, the coefficients on $Emissions_t \times AQI_t$ are negative and statistically significant at the 1% level, indicating that mutual fund managers sell more shares of high emission firms' stocks when they are exposed to higher levels of air pollution (i.e., higher *AQI*). These results, which are consistent with our baseline findings, suggest that our baseline findings are not driven simply by the falling share prices of high emission firms' stocks.

3.4.2. *Local Bias and the Effect of Air Pollution*

Mutual funds tend to bias their holdings toward local stocks and trade local stocks at an information advantage (Coval and Moskowitz, 2001). This local bias may explain our results if local air pollution is correlated with local economic conditions that affect local firms' fundamentals. To examine whether firms belonging to funds' local investments drive our results, we partition our sample into two groups based on whether the distance between a mutual fund's location and the firm's headquarters is more than or less than 100 miles. Specifically, we obtain historical information on firms' headquarters locations (the longitude and latitude coordinates) from Bill MacDonald's website, supplemented with information from SEC filings provided by the WRDS SEC Analytics Suite and calculate the distance between a firm's headquarters and its mutual fund's headquarters. We then group our sample into two groups, where the low-distance group comprises fund-firm pairs for which the distance is less than or equal to 100 miles and the high-distance group includes fund-firms for which the distance is greater than 100 miles.

We estimate our baseline regression for each subsample and report the results in Table 12. In Column 1, we report the regression results for the subsample associated with fund-firm distances that are less than or equal to 100 miles. The regression results reported in Column 2 use the subsample associated with fund-firm distances that are greater than 100 miles. We find that, in both subsamples, the coefficients on $Emissions_t \times AQI_t$ are negative and statistically significant at the 1% level. Although the coefficient on $Emissions_t \times AQI_t$ is greater in magnitude for the low-distance subsample, the significant coefficient on $Emissions_t \times AQI_t$ in the high-distance subsample suggests that our findings are unlikely driven by the local bias of mutual funds.

[Insert Table 12 About Here]

3.4.3. *Analyst Optimism and Local Air Pollution*

The results we have reported thus far are consistent with the notion that local air pollution causes fund managers to overestimate climate-transition risks their portfolio firms are exposed to, as predicted by the salience hypothesis. However, the evidence is not direct as fund managers' beliefs are not observable and we can only infer such belief changes from their portfolio adjustment. Alternatively, our findings could be explained by the "preference" channel, that is, exposure to air pollution increases fund managers' non-pecuniary benefits (disutility) of investing in green (brown) assets.

To provide more direct evidence of the salience channel and help distinguish this from the preference-based channel, we examine earnings forecasts issued by individual equity analysts. Analysts' earnings forecasts arguably provide a more direct measure of their beliefs about the covered firms' fundamentals and have been used by several recent studies to test belief-based behavioral finance models (Bordalo, Gennaioli, Porta, and Shleifer, 2019; Bouchaud, Krueger, Landier, and Thesmar, 2019).[35] Specifically, the salience hypothesis predicts that earnings forecasts of high-emission firms by analysts exposed to air pollution should be more pessimistic compared to forecasts on the same firm by nonexposed analysts.[36] Moreover, because analysts' outputs are widely used by investors for making investment decisions, understanding whether air pollution affects analyst forecasts also provide corroborative evidence for the stock return results that we show in Section 3.3.5.

A major challenge for this test is the lack of data on analyst locations, which are not available through standard databases such as IBES. We thus hand-collect information on the locations of all analysts covered in the IBES database by searching analysts' LinkedIn profiles and their affiliated companies' websites. This process yields 1,455 unique analysts with valid county location information over the period spanning January 2015 through December 2018. The final dataset contains 669,349 analyst-firm-month observations. We construct a measure of analyst forecast optimism, *Optimism,* which is computed as an analyst's forecasted EPS minus the firm's actual EPS, scaled by the firm's

[35] Analysts are usually assigned by their brokerage firms to cover a particular sector and set of firms, and their firm-level coverage decisions also reflect their expectation of firm performance (Lee and So, 2017).
[36] Similar to the mutual fund setting, the analyst setting also allows us to isolate the effect of air pollution on individual beliefs from its confounding effect on firm fundamentals, as the same firm are usually covered by multiple analysts who could be located in different regions.

stock price in the month before the earnings announcement. As before, we calculate the air quality index in a given month in an analyst's county by averaging the *AQI* of all monitoring stations (*AQI Analyst*). We then estimate the regression of *Optimism* measured in month t+1 on *Emissions* × *AQI Analyst, AQI Analyst,* weather variables, and fixed effects. We consider alternative fixed effects such as analyst fixed effects, county fixed effects, stock × year × month fixed effects, analyst × year fixed effects, and analyst × stock fixed effects. The stock × year × month fixed effects ensure that our results are not confounded by any time-varying unobservable stock characteristics that are correlated with forecast optimism. Similarly, including analyst × year fixed effects ensures that our results are not confounded by yearly changes related to analyst attributes.

In Table 13, we report the estimation results. With all models, we observe a negative and significant coefficient on *Emissions* × *AQI Analyst*, suggesting that analysts' forecasts regarding high-emission firms are less optimistic when the analysts are exposed to poor air quality conditions in their counties than the forecasts of other non-exposed analysts covering the same firm. Again, these results are consistent with our evidence pertaining to fund managers and further validate the salience bias channel as a driver of managers' carbon-divestment actions.

[Insert Table 13 About Here]

3.4.4. Firm Environmental, Social, and Governance Scores (ESG)

We next use a firm's Environmental, Social, and Governance (ESG) score as another laboratory in which to test our hypothesis. If local air pollution raises fund managers' awareness of environmental risk, we expect to find similar effects using firms' environmental scores (*EScore*). By contrast, these effects should be attenuated or disappear when we consider social and governance scores (*S&G Score*), which are not directly related to fund managers' concerns about environmental risk. To examine this prediction, we obtain firm-level data on ESG scores from the Sustainalytics database. Khan, Serafeim, and Yoon (2016) show that, while a firm is rated based on a large number of ESG issues, only a handful of these issues are deemed material. Following Khan, Serafeim, and Yoon (2016), we use the materiality map from the Sustainability Accounting Standard Board (SASB) to identify ESG issues that are financially material for 79 industries. Each SASB material issue can be evaluated using multiple Sustainalytics metrics – each metric ranges from 0 to 100 in value, where 100 represents the best score. To obtain the scores for these metrics, we merge SASB material issues with relevant ESG metrics from Sustainalytics. To avoid any confounding effects resulting from Sustainalytics's own weighting schemes, we use the historical raw (unweighted) scores. We standardize these scores to ensure that they are comparable across industries. The final (aggregate) material *EScore* (S and G scores) for each firm in a given month is then the average of individual standardized scores. To avoid look-ahead bias, we lag these scores by one year in our regressions.

In Appendix Table A5, we estimate our baseline regression but replace *Emissions* with either *EScore* or *S&G Score*. We find that the coefficient on *EScore* × *AQI* is positive and statistically significant at the 1% level, suggesting that fund managers increase the portfolio weights of firms with superior environmental performance as local air quality worsens. By contrast, we find that the coefficient on *S&G Score* × *AQI* is insignificant at all conventional levels. These results are consistent with our prediction that local air pollution will heighten fund managers' concerns about firm environmental risk but not their concerns about social or governance risk.

3.4.5. Paris Agreement in 2015

Choi, Gao, Jiang, and Zhang (2021) show that financial institutions reduce their exposure to stocks of high-emission industries following the Paris Agreement that was signed in 2015. To examine whether our results are concentrated in the post-Paris Agreement period when public concerns about climate risks rose significantly, we split our sample into two subsample periods, i.e., before and after 2015. We report the results in Appendix Table A6. Column 1 presents the results for the sample period spanning 2005 through 2015. Column 2 displays the results for the post-Paris Agreement period, i.e., 2016 through 2018. We find that, the coefficients on *Emissions* × *AQI* are negative and significant at the 1% level in both subsamples and are similar in magnitude. These results suggest that local environmental conditions in addition to salient public events can significantly raise investor concerns about climate-transition risks.[37]

4. Conclusion

In this study, we examine whether exposure to local air pollution affects fund managers' divestment of carbon-polluting firms. We measure a fund manager's exposure to air pollution using the average aggregate *AQI* across all monitoring stations located within a five-mile radius of a mutual fund's headquarters location. We find that, when the air quality in funds' local areas is poor, fund managers reduce their funds' holdings in stocks of high-emission firms. The finding is consistent with the salience hypothesis according to which exposure to local air pollution elevates fund managers' concerns about carbon risk, which in turn drives their divestment decisions. Our baseline results remain robust when we employ alternative measures of carbon emissions or high-dimensional fixed effects to control for unobserved heterogeneity across funds and firms. Using strong winds as a source of exogenous variation in air quality, we show that the effects of local air pollution on funds' portfolio weights of high-emission firms are likely to be causal.

Moreover, we provide further evidence that collectively supports the salience hypothesis. First, we find that the effects are more pronounced for Scopes 2 and 3 emissions, which are generally less salient than Scope 1 emissions that are widely

[37] Fund managers may cater to their clients who are also exposed to air pollution and demand their funds to divest from carbon-intensive firms. An implication of this explanation is that the effects of local air pollution on funds' divestment are stronger among funds that are more vulnerable to fund outflows. To examine this prediction, for each year, we split funds in our sample into two groups based on the median value of their previous year fund flows. If our results are driven by catering, we expect the effects to be concentrated among funds with below-median flows. We find that the effects of local air pollution are strong for both types of funds. In fact, the coefficient on *Emissions* × *AQI* is -0.018 (t-statistic = -5.79) for funds with below-median flows, whereas this coefficient is -0.020 (t-statistic = -7.27) for funds with above-median flows—a result that is inconsistent with the catering explanation.

reported and used in exclusionary screenings by institutional investors. Second, we show that fund managers located in states with a pro-environmental attitude are more likely to respond to local air pollution by reducing their funds' holdings of carbon-emitting firms. Third, compared with managers who have experienced poor air quality historically, fund managers who are not accustomed to poor air quality respond more strongly to air pollution. Fourth, we find that the effects of air pollution on portfolio weights becomes insignificant after three quarters. Finally, our portfolio analyses show that stocks of high-emission firms that are underweighted subsequently outperform stocks that are overweighted by exposed funds, suggesting that funds exposed to air pollution tend to overreact by selling stocks of high emission firms. This overreaction is costly to fund investors.

Our findings provide new insights into the factors that drive institutional investors' divestment from carbon-intensive assets. Existing studies emphasize persistent characteristics at the fund or fund-manager level (such as UN PRI signatories or political affiliation) in driving their carbon divestment. Our study shows that transitory environmental factors can also exert an important impact on fund managers' carbon divestment decisions by raising investors' concerns about climate-transition risks.

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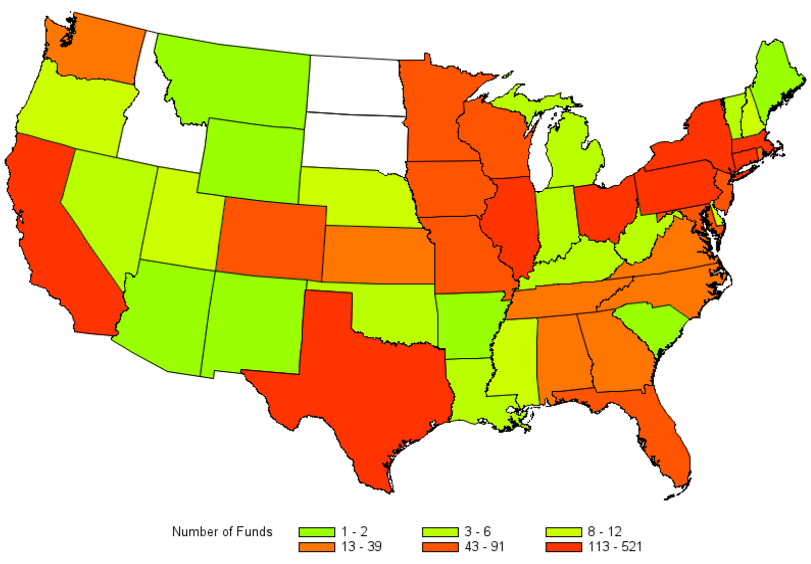
Figure 1: Geographic Distribution of Mutual Funds between 2005 and 2018

This figure depicts the number of mutual funds in the U.S. over the full sample period (Panel A) as well as mutual funds that were exposed to poor air quality conditions. The sample contains a total of 2,291 unique funds, whose locations are represented in Panel A. Panel B displays the total number of fund-quarters in which the air quality index (*AQI*) is above 50. According to the EPA, an AQI value of 50 or below represents good air quality. An *AQI* between 51 and 100 may be a risk for some people, especially those who are sensitive to air pollution. An *AQI* above 100 is typically considered unhealthy.

Panel A: Locations of Unique Mutual Funds in the Sample



Panel B: Fund-Quarters with Moderate or Unhealthy Air Quality

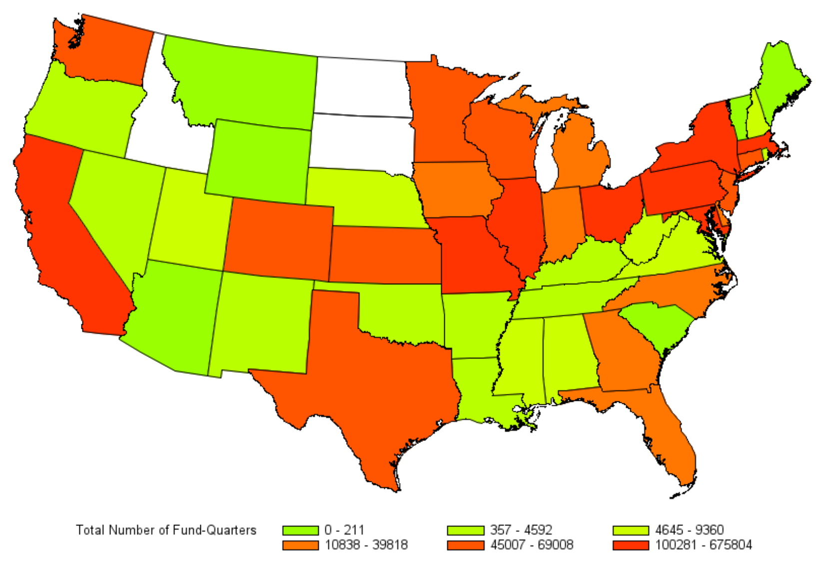


Table 1: Summary Statistics

The summary statistics include the sample means, the 25th percentile, the medians, the 75th percentile, and the standard deviation of the key variables used in this study. These variables are defined in Appendix Table A1. The sample contains 2,479,757 observations. The sample period spans 2005 through 2018.

Variable	Mean	25th	Median	75th	Std. Dev.
Weight	0.795	0.020	0.409	1.196	1.007
AQI (scaled by 100)	0.461	0.360	0.439	0.538	0.147
Emissions	13.840	12.453	13.843	15.328	2.038
TSun (log)	3.598	0.000	5.337	5.928	2.841
Wind (log)	3.530	3.403	3.552	3.684	0.204
Tmp (℃)	9.827	7.767	11.348	19.272	2.451
Ln(Fund Size)	5.979	4.722	6.007	7.188	1.702
Exp Ratio	0.010	0.008	0.010	0.013	0.004
Turn Ratio	0.790	0.360	0.650	1.040	0.616
Fund Ret	0.005	-0.015	0.005	0.030	0.046
Fund Flow	-0.003	-0.015	-0.005	0.005	0.044
Size	9.188	8.089	9.064	10.205	1.496
Ln(BM)	0.350	0.198	0.315	0.474	0.212
Momentum	0.151	-0.063	0.122	0.320	0.363
Return on Asset	0.139	0.085	0.133	0.187	0.092
Sales Growth	0.089	-0.009	0.065	0.155	0.206
Leverage	0.151	0.055	0.122	0.215	0.128

Table 2: Main Results – Portfolio Weights of Polluting Firms and Air Quality

This table reports the results of the following fund-firm-quarter level regressions that examine the effects of air quality on mutual funds' portfolio weights of polluting firms,

$$Weight_{f,i,t+1} = \beta_0 + \beta_1 Emissions_{i,t} \times AQI_{f,t} + \beta_2 AQI_{f,t} + \beta_3 Emissions_{i,t} + \delta' X_{f,t} + \gamma' S_{i,t} + \varphi_f + \mu_i + \theta + \tau_t + \varepsilon_{p,t}$$

where $Weight_{f,i,t+1}$ is the weight of a stock *i* in mutual fund *f*'s portfolio at the end of quarter *t*+1, calculated as the dollar holdings of a stock divided by the total dollar holdings of all stocks in the mutual fund's portfolio. $Emissions_{i,t}$ is the natural logarithm of the sum of firm *i*'s total carbon emissions of all three scopes (i.e., Carbon Emission Scopes 1, 2, and 3). $AQI_{f,t}$ is the average aggregate AQI across all monitoring stations located within a five-mile radius of mutual fund *f*'s location over quarter *t*. The aggregate AQI is the average of air quality indexes based on five major air pollutants: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and fine particulate matter smaller than 2.5 micrometers in diameter. For each air pollutant, we first obtain the monthly AQI around each fund's location as the maximum daily index over a given month across all monitoring stations located within a five-mile radius of a fund's headquarters. For each fund's location, we then calculate the quarterly AQI for an air pollutant as the average of the monthly AQI over a given quarter. $X_{f,t}$ and $S_{i,t}$ represent the sets of fund-level control variables and stock-level control variables, respectively. φ_f, μ_i, θ, and τ_t are vectors for fund, stock, fund's county, and year-quarter fixed effects. For Panel A, we estimate the above regression controlling for alternative fixed effects. For Columns 1, 2, and 4, we include fund, stock, fund's county, and year-quarter fixed effects. For Columns 3 and 5, we include fund, stock, fund's county × year-quarter fixed effects. In Panel B, we examine the nonlinear effects of *AQI* by replacing *AQI* in the regressions associated with Panel A with one of the three dummy variables, *High AQI*, *Med AQI*, and *Low AQI*, which are equal to 1 if the *AQI* at a fund's location is above 100, between 50 and 100, and below 50, respectively. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Table 2: continued

Panel A: Portfolio Weights of Polluting Firms and Air Quality

	Dependent Variable: $Weight_{t+1}$		
Variable	(1)	(2)	(3)
$Emissions_t \times AQI_t$	-0.011***	-0.015***	-0.013***
	(-4.124)	(-4.353)	(-3.636)
AQI_t	0.155***	0.199***	0.163***
	(4.492)	(4.340)	(3.544)
$Emissions_t$	0.093***	0.092***	0.075***
	(44.544)	(31.141)	(7.068)
$TSun_t$		-0.000	-0.018***
		(-0.342)	(-6.616)
Tmp_t		0.005	0.016**
		(1.350)	(2.488)
$Wind_t$		-0.041**	-0.090**
		(-2.173)	(-2.158)
$Emissions_t \times TSun_t$			0.001***
			(6.507)
$Emissions_t \times Wind_t$			0.003
			(1.208)
$Emissions_t \times Tmp_t$			-0.001**
			(-1.984)
$Ln(Fund\ Size)_t$		-0.002	-0.002
		(-0.433)	(-0.465)
$Exp\ Ratio_t$		3.782**	3.806**
		(1.967)	(1.979)
$Turn\ Ratio_t$		-0.097***	-0.097***
		(-16.938)	(-16.899)
$Fund\ Ret_t$		0.304***	0.306***
		(5.676)	(5.706)
$Fund\ Flow_t$		-0.030	-0.029
		(-0.742)	(-0.719)
$Size_t$		0.031***	0.031***
		(14.358)	(14.450)
$Ln(BM)_t$		-0.381***	-0.381***
		(-54.825)	(-54.827)
$Momentum_t$		0.072***	0.072***
		(23.769)	(23.773)
$Return\ on\ Asset_t$		0.083***	0.080***
		(6.532)	(6.370)
$Sales\ Growth_t$		0.081***	0.081***
		(24.478)	(24.555)
$Leverage_t$		-0.406***	-0.405***
		(-36.233)	(-36.143)
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes

Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	4,614,369	2,479,757	2,479,757
Adj. R-squared	0.449	0.455	0.455

Panel B: Nonlinear Effects of AQI

	Dependent Variable: $Weight_{t+1}$		
Variable	(1)	(2)	(3)
$Emissions_t \times Low\ AQI_t$	0.003**		
	(2.496)		
$Emissions_t \times Med\ AQI_t$		-0.002*	
		(-1.885)	
$Emissions_t \times High\ AQI_t$			-0.018***
			(-2.854)
$Low\ AQI_t$	-0.041***		
	(-2.839)		
$Med\ AQI_t$		0.034**	
		(2.305)	
$High\ AQI_t$			0.208***
			(2.850)
$Emissions_t$	0.082***	0.085***	0.083***
	(34.860)	(35.733)	(36.296)
$TSun_t$	-0.000	-0.000	-0.000
	(-0.368)	(-0.363)	(-0.342)
Tmp_t	0.005	0.005	0.005
	(1.315)	(1.301)	(1.333)
$Wind_t$	-0.038**	-0.038**	-0.040**
	(-2.033)	(-2.027)	(-2.128)
Other Control Variables	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.455	0.455	0.455

Table 3: Endogeneity - High-Dimensional Fixed Effects

This table reports the results of the baseline regressions associated with Table 2 using alternative high-dimensional fixed effects. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Weight_{t+1}$					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
$Emissions_t \times AQI_t$	-0.014***	-0.012***	-0.014***	-0.011**	-0.012***	-0.011***
	(-2.801)	(-4.836)	(-4.106)	(-2.216)	(-4.961)	(-3.223)
AQI_t	0.152**	0.118***	0.045	0.114*	0.128***	0.000
	(2.431)	(3.633)	(0.617)	(1.783)	(3.808)	(0.005)
$TSun_t$	-0.002*	-0.000	-0.196**	-0.001	-0.004	-0.215**
	(-1.704)	(-0.098)	(-2.111)	(-0.172)	(-1.511)	(-2.319)
Tmp_t	0.008**	0.008***	0.011	0.026***	0.014*	0.028***
	(2.099)	(7.099)	(1.339)	(3.909)	(1.932)	(2.996)
$Wind_t$	-0.038**	-0.039***	-0.132	0.023	0.025	-0.143
	(-2.130)	(-7.311)	(-1.268)	(0.418)	(0.700)	(-1.311)
$Emissions_t \times TSun_t$				-0.000	0.000	0.001***
				(-0.296)	(1.466)	(7.733)
$Emissions_t \times Wind_t$				-0.004	-0.000	0.001
				(-1.079)	(-0.854)	(0.259)
$Emissions_t \times Tmp_t$				-0.001***	-0.005*	-0.001***
				(-3.125)	(-1.766)	(-3.292)
Other Control Variables	Yes	Yes	Yes	Yes	Yes	Yes
Fund County FEs	Yes	Yes	No	Yes	Yes	No
Fund × Stock FEs	Yes	Yes	No	Yes	Yes	No
Year-Quarter FEs	Yes	No	No	Yes	No	No
Stock×Year×Quarter FEs	No	Yes	No	No	Yes	No
Fund County×Year×Qtr FEs	No	No	Yes	No	No	Yes
Fund FEs	No	No	Yes	No	No	Yes
Stock FEs	No	No	Yes	No	No	Yes
Number of Obs	2,479,757	2,479,757	2,479,757	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.623	0.653	0.472	0.623	0.653	0.472

Table 4: Endogeneity - Strong Winds and Reductions in *AQI*

Panel A reports the results of two-stage least squares (2SLS) regressions using strong winds as the instrumental variable for *AQI*. *Strong Wind* is a dummy variable that is equal to one if a strong wind occurs at a fund's location and zero otherwise. The wind at a fund's location is considered strong if the average wind speed over a quarter is two standard deviations above the previous year's average wind speed. In the first stage, we obtain the fitted value of AQI_t ($\widehat{AQI_t}$) by estimating the regression of AQI_t on $StrongWind_t$, the interaction term between $StrongWind_t$ and $Emissions_t$, control variables, and fixed effects. We also obtain the fitted value of $Emissions_t \times AQI_t$, i.e., $\widehat{Emissions_t \times AQI_t}$, by estimating the regression of $Emissions_t \times AQI_t$ on $StrongWind_t$, the interaction term between $StrongWind_t$ and $Emissions_t$, control variables, and fixed effects. In the second stage, we regress $Weight_{t+1}$ on $\widehat{Emissions_t \times AQI_t}$, $\widehat{AQI_t}$, and the same set of control variables and fixed effects as in the first stage. In Panel B, we report the results of the placebo tests for the instrumental-variable approach, which examines whether strong winds can affect $Weight_{t+1}$ directly even when *AQI* is low. The sample is split into two subsamples based on *AQI* in quarter *t*-1. For each subsample, we estimate the regression of $Weight_{t+1}$ on $Emissions_t \times StrongWind_t$, $StrongWind_t$ control variables, and fixed effects. In Column 1, we report the results for the subsample with AQI_{t-1} lower than 100. In Column 2, we report the results for the subsample with AQI_{t-1} greater than or equal to 100. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Panel A: Strong Winds as Instrumental Variable

	First Stage		Second Stage
	AQI_t	$Emissions_t \times AQI_t$	$Weight_{t+1}$
Variable	(1)	(2)	(3)
$StrongWind_t$	-0.086***	-1.231***	
	(-17.312)	(-18.657)	
$Emissions_t \times StrongWind_t$	0.005***	0.099***	
	(15.213)	(19.874)	
$\widehat{Emissions_t \times AQI_t}$			-0.052***
			(-4.044)
$\widehat{AQI_t}$			0.484***
			(2.961)
$Emissions_t$	-0.003***	-0.694***	0.047***
	(-5.472)	(-107.939)	(5.344)
$TSun_t$	0.007***	0.024***	-0.004***
	(90.213)	(21.861)	(-3.731)
Tmp_t	0.081***	1.054***	0.025*
	(235.253)	(241.657)	(1.695)
$Ln(Fund\ Size)_t$	-0.003***	0.035***	-0.002*
	(-34.701)	(9.844)	(-1.748)
$Exp\ Ratio_t$	-1.500***	30.902***	6.072***
	(-32.706)	(16.254)	(7.886)
$Turn\ Ratio_t$	-0.018***	0.109***	-0.082***
	(-70.169)	(19.883)	(-20.682)

Fund Ret$_t$	0.106***	1.642***	0.276***
	(26.250)	(31.535)	(10.374)
Fund Flow$_t$	0.039***	0.403***	-0.024*
	(11.959)	(9.180)	(-1.775)
Size$_t$	-0.003***	-0.065***	0.031***
	(-7.162)	(-11.347)	(17.684)
Ln(BM)$_t$	-0.008***	-0.013	-0.369***
	(-5.383)	(-0.692)	(-69.482)
Momentum$_t$	-0.001***	-0.006	0.071***
	(-3.366)	(-1.080)	(45.985)
Return on Asset$_t$	0.006*	0.297***	0.081***
	(1.853)	(7.044)	(6.323)
Sales Growth$_t$	0.003***	-0.021**	0.078***
	(3.283)	(-2.097)	(26.343)
Leverage$_t$	-0.005*	-0.270***	-0.425***
	(-1.687)	(-7.285)	(-40.326)
Cragg-Donald Wald *F*-statistics	36.556		
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.572	0.691	0.458

Panel B: Placebo Tests

	Dependent Variable: *Weight$_{t+1}$*	
	(1)	(2)
Variable	*AQI$_{t-1}$<100*	*AQI$_{t-1}$≥100*
Emissions$_t$ × *StrongWind$_t$*	-0.003	0.011***
	(-0.947)	(2.651)
Emissions$_t$	0.082***	0.076***
	(34.061)	(6.609)
StrongWind$_t$	0.019	-0.649***
	(0.508)	(-3.429)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	2,255,771	53,642
Adj. R-squared	0.458	0.560

Table 5: Placebo Analyses Using Distant *AQI* and Future *AQI*

Panel A reports the results of placebo tests that use the *AQI* measured at distant monitoring stations. $AQI[6, 100]_t$ is the average aggregate *AQI* across all monitoring stations located between 6 miles and 100 miles of a mutual fund's location over quarter *t*. $AQI(100, 200]_t$ is the average aggregate *AQI* across all monitoring stations located between 100 miles and 200 miles of a mutual fund's location over quarter *t*. $AQI(> 200)_t$ is the average aggregate *AQI* across all monitoring stations located more than 200 miles of a mutual fund's location over quarter *t*. Panel B reports the results of placebo tests that use the *AQI* measured in future years. *AQI_Nxt1yr* and *AQI_Nxt2yr* are the *AQI* of the same quarter as *AQI* but measured in the following one and two years, respectively. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively. The variables are defined in Appendix Table A1.

Panel A: Placebo Analysis Using Distant AQI

	Dependent Variable: $Weight_{t+1}$		
Variable	(1)	(2)	(3)
$Emissions_t \times AQI_t$	-0.014***	-0.011**	-0.011**
	(-3.456)	(-2.480)	(-2.550)
$Emissions_t \times AQI[6, 100]_t$	0.000	-0.000	-0.000
	(0.307)	(-0.164)	(-0.349)
$Emissions_t \times AQI(100, 200]_t$		-0.000	-0.000
		(-0.144)	(-0.350)
$Emissions_t \times AQI(> 200)_t$			0.000
			(0.722)
AQI_t	0.170***	0.145***	0.160***
	(3.330)	(2.648)	(2.900)
$AQI[6, 100]_t$	0.000	0.001	0.001
	(0.484)	(1.206)	(1.480)
$AQI(100, 200]_t$		0.000	0.000
		(0.191)	(0.556)
$AQI(> 200)_t$			0.003**
			(2.014)
$Emissions_t$	0.091***	0.093***	0.089***
	(26.487)	(22.088)	(14.143)
Other Control Variables	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.460	0.455	0.455

Table 5: continued

Panel B: Placebo Analysis Using Future AQI

	Dependent Variable: $Weight_{t+1}$	
Variable	(1)	(2)
$Emissions_t \times AQI_t$	-0.017***	-0.013***
	(-2.705)	(-2.807)
$Emissions_t \times AQI\_Nxt1yr$	-0.003	
	(-0.485)	
$Emissions_t \times AQI\_Nxt2yr$		-0.008
		(-1.445)
AQI_t	0.212**	0.163**
	(2.576)	(2.576)
AQI_Nxt1yr	0.036	
	(0.446)	
AQI_Nxt2yr		0.097
		(1.274)
$Emissions_t$	0.097***	0.095***
	(32.008)	(27.338)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	2,245,121	2,035,848
Adj. R-squared	0.459	0.456

Table 6: Air Pollution and Different Scopes of Carbon Emissions

This table reports the results of the regressions using firm carbon emissions of varying scopes. We repeat the regression associated with Column 1 of Table 2 Panel A but replace the *Emissions* measure with three scopes of the carbon emission measure, separately. For Columns 1 through 3, $Emissions_t$ is defined as the natural logarithm of firm *i*'s total carbon emissions of Scopes 1, 2, and 3, respectively. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Weight_{t+1}$		
	(1)	(2)	(3)
Variable	Scope 1	Scope 2	Scope 3
$Emissions_t \times AQI_t$	0.001	-0.010***	-0.020***
	(0.342)	(-2.811)	(-5.033)
AQI_t	-0.022	0.098***	0.258***
	(-0.865)	(2.618)	(5.115)
$Emissions_t$	0.016***	0.030***	0.104***
	(11.708)	(15.315)	(32.268)
Other Control Variables	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.454	0.454	0.455

Table 7: State's Attitude toward Environmental Regulations

This table reports the results of subsample tests based on the surveyed attitudes toward stricter environmental regulations in U.S. states, which we obtain from the 2014 Religious Landscape Survey conducted by the Pew Research Center. *Pro Env1* is measured as the number of survey participants in a state that supports stricter environmental laws and regulations scaled by the total number of survey participants in the state (which include supporters, opponents, and those with a neutral view). *Pro Env2* is measured as the number of survey participants in a state that support stricter environmental laws and regulations scaled by the sum of the number of supporters and opponents of stricter environmental laws and regulations in the state. For Columns 1 and 2, the sample is split into two subsamples based on the median value of state-level *Pro Env1.* For Columns 3 and 4, the sample is split into two subsamples based on the median value of state-level *Pro Env2*. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Weight_{t+1}$		Dependent Variable: $Weight_{t+1}$	
	(1)	(2)	(3)	(4)
Variable	High *Pro Env1*	Low *Pro Env1*	High *Pro Env2*	Low *Pro Env2*
$Emissions_t \times AQI_t$	-0.027***	-0.000	-0.025***	0.001
	(-5.762)	(-0.014)	(-4.069)	(0.131)
AQI_t	0.274***	0.160**	0.101***	0.079***
	(4.687)	(2.077)	(21.840)	(20.036)
$Emissions_t$	0.101***	0.078***	0.191**	0.120**
	(26.165)	(17.549)	(2.232)	(2.219)
Z-statistics	-3.664***		-3.419***	
Other Control Variables	Yes	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes	Yes
Number of Obs	1,434,240	1,045,517	1,266,489	1,213,268
Adj. R-squared	0.443	0.475	0.443	0.471

Table 8: Funds' Historical Exposure to Air Pollution

This table reports the results of subsample tests based on a mutual fund's historical exposure to air pollution. Historical *AQI* is measured as the moving average of *AQI* over the previous year. Column 1 reports the regression results for the subsample with historical *AQI* lower than 100. Column 2 reports the regression results for the subsample with historical *AQI* greater than or equal to 100. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Weight_{t+1}$	
	(1)	(2)
Variable	Historical *AQI* <100	Historical *AQI* ≥100
$Emissions_t \times AQI_t$	-0.015***	-0.001
	(-8.273)	(-0.047)
AQI_t	0.217***	-0.065
	(8.590)	(-0.822)
$Emissions_t$	0.090***	0.096***
	(41.815)	(10.149)
Z-statistics	-2.332***	
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	2,258,661	220,752
Adj. R-squared	0.458	0.586

Table 9: Long-Run Portfolio Responses

This table reports the results of the regressions that examine mutual funds' long-run portfolio responses to local air pollution. We repeat the regression associated with Column 1 of Table 2 Panel A but replace the dependent variables with the weight measured in future quarters. The dependent variables for Columns 1 through 3 are $Weight_{t+2}$, $Weight_{t+3}$, and $Weight_{t+4}$, which is the weight of a stock in a mutual fund's portfolio at the end of quarters t+2, t+3, and t+4, respectively. Standard errors are clustered at the fund-year-quarter level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Variable	$Weight_{t+2}$ (1)	$Weight_{t+3}$ (2)	$Weight_{t+4}$ (3)
$Emissions_t \times AQI_t$	-0.013***	-0.009**	-0.004
	(-3.584)	(-2.421)	(-1.163)
AQI_t	0.181***	0.122***	0.056
	(3.873)	(2.647)	(1.326)
$Emissions_t$	0.098***	0.077***	0.054***
	(30.794)	(23.960)	(19.095)
Other Control Variables	Yes	Yes	Yes
Fund FEs	Yes	Yes	Yes
Stock FEs	Yes	Yes	Yes
Fund County FEs	Yes	Yes	Yes
Year-Quarter FEs	Yes	Yes	Yes
Number of Obs	2,479,757	2,479,757	2,479,757
Adj. R-squared	0.404	0.373	0.360

Table 10: Impact on Stock Returns

This table reports quarterly value-weighted portfolio returns that are adjusted for Fama and French's (2014) six risk factors (market, size, book-to-market, profitability, investment, and momentum factors). In each year, we first identify top polluting firms by sorting firms into quintiles based on their carbon emissions measured in the previous year, where firms in quintile 5 with high *Emissions* values are deemed Top Polluters. Independently, for each quarter, a fund is deemed to be exposed to poor air quality if the *AQI* at the fund's area measured in quarter t-1 is at least one standard deviation above its prior year's average (Exposed Funds); all other funds are considered Unexposed Funds. We then compute the change in weights of Top Polluters in Exposed Funds' portfolios (Unexposed Funds' portfolios) as $Ln\left(Weight_{f,i,t}\right) - Ln(Weight_{f,i,t-2})$. In Panel A, for each Top Polluter stock, we compute the average change in weights across Exposed Funds. We then sort stocks into quintiles based on the average change in stock weights by Exposed Funds, where quintile 1 contains Top Polluter stocks that exhibit the lowest average change in weight and quintile 5 contains stocks that exhibit the highest average change in weight by Exposed Funds. The heading above each column represents the holding period in months. In Panel B, we repeat the portfolio construction procedure but uses the change in weight by Unexposed Funds as the sorting variable. Panel C displays the differences in returns between Panel A and Panel B. In Panel D, we report average firm characteristics (operating profitability and investment) of stocks that are included in the portfolios associated with the portfolios in Panel A. *t-statistics* computed using Newey-West standard errors with 5 lags are reported in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Exposed Funds' Portfolios of Top Polluting Firms

	Window			
Portfolio	[-15, -4]	[1, 12]	[1, 24]	[1, 36]
1 (Most Underweighted)	-0.574***	0.173	0.174*	0.151
	(-5.112)	(1.536)	(1.649)	(1.429)
2	-0.133**	0.033	-0.005	-0.042
	(-2.090)	(0.417)	(-0.067)	(-0.552)
3	0.140**	0.013	-0.006	-0.023
	(2.192)	(0.233)	(-0.104)	(-0.418)
4	0.454***	-0.041	-0.028	-0.034
	(5.598)	(-0.606)	(-0.476)	(-0.624)
5 (Most Overweighted)	0.559***	-0.193*	-0.151	-0.120
	(4.782)	(-1.759)	(-1.571)	(-1.380)
1 minus 5	-1.133***	0.366**	0.324**	0.272**
	(-6.434)	(2.406)	(2.500)	(2.159)

Panel B: Unexposed Funds' Portfolios of Top Polluting Firms

	Window			
Portfolio	[-15, -4]	[1, 12]	[1, 24]	[1, 36]
1	-0.630***	-0.016	-0.032	-0.055
	(-3.453)	(-0.111)	(-0.242)	(-0.417)

2	-0.350**	0.019	-0.016	-0.041
	(-2.351)	(0.158)	(-0.136)	(-0.337)
3	-0.141	0.014	0.001	-0.019
	(-1.009)	(0.117)	(0.007)	(-0.164)
4	0.187	-0.079	-0.087	-0.075
	(1.187)	(-0.553)	(-0.635)	(-0.574)
5	0.392**	-0.059	-0.052	-0.070
	(2.035)	(-0.376)	(-0.343)	(-0.482)
1 minus 5	-1.022***	0.044	0.020	0.015
	(-5.529)	(0.368)	(0.209)	(0.189)

Panel C: Differences between Exposed Funds' Portfolios and Unexposed Funds' Portfolios

	Window			
Exposed - Unexposed	[-15, -4]	[1, 12]	[1, 24]	[1, 36]
1	0.056	0.189	0.206	0.206
	(0.297)	(1.130)	(1.300)	(1.289)
2	0.217	0.014	0.011	-0.001
	(1.550)	(0.098)	(0.085)	(-0.008)
3	0.280**	-0.001	-0.007	-0.003
	(2.310)	(-0.005)	(-0.057)	(-0.029)
4	0.266*	0.038	0.059	0.041
	(1.913)	(0.292)	(0.457)	(0.332)
5	0.167	-0.134	-0.099	-0.050
	(1.009)	(-0.968)	(-0.742)	(-0.384)
1 minus 5	-0.110	0.323**	0.305**	0.257**
	(-0.692)	(2.026)	(2.349)	(2.004)

Panel D: Firm Fundamentals of Stocks in Exposed Funds' Portfolios

	Profitability		Investment	
Portfolio	Year *t*-1	Year *t*+1	Year *t*-1	Year *t*+1
1	-3.236***	-2.777***	1.099***	0.776**
	(-6.800)	(-6.040)	(2.670)	(2.560)
2	-3.090***	-3.240***	0.650***	0.790**
	(-6.420)	(-4.910)	(2.840)	(2.410)
3	-2.490***	-2.730***	0.640***	0.540**
	(-14.610)	(-5.280)	(2.960)	(2.240)
4	-3.570***	-2.920***	0.780***	0.760***
	(-4.570)	(-6.040)	(2.850)	(3.000)
5	-8.960	-3.710***	0.470***	0.740***
	(-1.550)	(-2.630)	(5.960)	(3.410)
1 minus 5	5.730	0.930	0.630	0.030
	(0.990)	(0.630)	(1.530)	(0.110)

Table 11: Alternative Measures of Fund Response to Air Pollution

This table reports the results from the regressions with alternative measures of fund response to air pollution. We repeat the regression associated with Column 1 of Table 2 Panel A but replace the dependent variables with two alternative measures of fund responses. For Column 1, the dependent variable, *Shares* Pct_{t+1}, is the ratio of the total number of shares of a stock held by a mutual fund in quarter t+1 to the total number of shares outstanding (in percentage). For Column 2, the dependent variable, *Traded* $Value_{t+1}$, is the dollar value of the shares of a stock traded (bought or sold) by a mutual fund during quarter t+1 (in millions). Standard errors are clustered at the fund-year-quarter level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Variable	*Shares* Pct_{t+1} (1)	*Traded* $Value_{t+1}$ (2)
$Emissions_t \times AQI_t$	-0.011***	-0.323***
	(-7.631)	(-4.406)
AQI_t	0.173***	4.079***
	(8.415)	(4.131)
$Emissions_t$	-0.014***	0.612***
	(-9.695)	(4.178)
$TSun_t$	-0.000	-0.078***
	(-1.302)	(-3.544)
Tmp_t	-0.001**	0.114***
	(-2.418)	(2.672)
$Wind_t$	-0.032***	2.224***
	(-11.239)	(8.953)
$Ln(Fund\ Size)_t$	0.096***	-0.712***
	(141.537)	(-16.904)
$Exp\ Ratio_t$	-1.146***	128.565***
	(-4.088)	(4.919)
$Turn\ Ratio_t$	-0.016***	-0.683***
	(-26.686)	(-19.763)
$Fund\ Ret_t$	-0.034***	0.255
	(-3.826)	(0.354)
$Fund\ Flow_t$	0.006	5.299***
	(0.940)	(20.052)
$Size_t$	-0.056***	-0.224***
	(-39.305)	(-2.952)
$Ln(BM)_t$	-0.010***	0.050
	(-2.749)	(0.228)
$Momentum_t$	-0.021***	-0.085
	(-20.412)	(-0.982)
$Return\ on\ Asset_t$	0.016*	-1.037
	(1.806)	(-1.468)
$Sales\ Growth_t$	0.003	-0.565***
	(0.992)	(-4.093)
$Leverage_t$	0.059***	-1.961***

	(6.138)	(-5.560)
Fund FEs	Yes	No
Stock FEs	Yes	No
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	2,479,289	2,127,771
Adj. R-squared	0.322	0.005

Table 12: Underweighting and Local Bias

This table reports the results of subsample tests based on the distance between a mutual fund's location and a firm's headquarters location. Column 1 reports the results for the subsample with fund-firm distances that are less than or equal to 100 miles. Column 2 reports the results for the subsample with fund-firm distances greater than 100 miles. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Weight_{t+1}$	
	(1)	(2)
Variable	Distance ≤100	Distance >100
$Emissions_t \times AQI_t$	-0.030***	-0.015***
	(-3.489)	(-4.230)
AQI_t	0.350***	0.200***
	(3.164)	(4.285)
$Emissions_t$	0.098***	0.094***
	(11.224)	(31.515)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	220,150	2,160,985
Adj. R-squared	0.465	0.460

Table 13: Analyst Forecast Bias and Local Air Pollution

This table reports the results from of analyst-firm-month-level regressions that examine the effects of local air quality on analysts' earnings forecast bias for polluting firms. $Optimism_{t+1}$ is forecast bias, defined as an analyst's forecasted EPS minus the actual EPS of a firm, scaled by the firm's stock price in the month before the earnings announcement. $AQI\ Analyst_t$ is the average aggregate AQI across all monitoring stations in the county where the analyst is located over month *t*. $TSun\ Analyst_t$ is the natural logarithm of 1 plus the average sunshine time in the analyst's county over month *t*. $Tmp\ Analyst_t$ is the average temperature in the analyst's county over month *t*. $Wind\ Analyst_t$ is the natural logarithm of 1 plus the average wind speed in the analyst's county over month *t*. For Column 1, we include analyst, analyst's county, and stock × year × month fixed effects. For Column 2, we include analyst's county, stock × year × month, and analyst × year fixed effects. For Column 3, we include analyst's county, stock × year × month, and analyst × stock fixed effects. For Column 4, we include analyst's county, stock × year × month, analyst × year, and analyst × stock fixed effects. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

	Dependent Variable: $Optimism_{t+1}$			
Variable	(1)	(2)	(3)	(4)
$Emissions_t \times AQI\ Analyst_t$	-0.020***	-0.021***	-0.011**	-0.015***
	(-4.151)	(-4.426)	(-2.086)	(-2.742)
$AQI\ Analyst_t$	0.272***	0.282***	0.158**	0.206***
	(4.290)	(4.512)	(2.279)	(2.964)
$TSun\ Analyst_t$	-0.002**	-0.003	-0.002***	-0.002
	(-2.151)	(-1.455)	(-2.825)	(-1.322)
$Tmp\ Analyst_t$	-0.000	-0.000	-0.000	-0.000
	(-0.553)	(-0.991)	(-1.050)	(-1.481)
$Wind\ Analyst_t$	0.014	0.004	0.011	0.003
	(1.243)	(0.366)	(1.003)	(0.284)
Analyst FEs	Yes	No	No	No
Analyst County FEs	Yes	Yes	Yes	Yes
Stock × Year × Month FEs	Yes	Yes	Yes	Yes
Analyst × Year FEs	No	Yes	No	Yes
Analyst × Stock FEs	No	No	Yes	Yes
Number of Obs	669,349	669,349	669,349	669,349
Adj. R-squared	0.427	0.431	0.444	0.446

Appendix Table A1: Variable Definition

Variable	Definition	Source
Weight	The weight of a stock in a mutual fund's portfolio at the end of a quarter, where the weight is calculated as the dollar holdings of a stock divided by the total dollar holdings of all stocks in the mutual fund's portfolio.	Thomson Reuters Mutual fund holdings (s12); CRSP
AQI	The average aggregate air quality index across all monitoring stations located within a five-mile radius of a mutual fund's location over a quarter. The aggregate air quality index is the average of air quality indexes based on five major air pollutants: ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and fine particulate matter smaller than 2.5 micrometers in diameter. For each individual pollutant, we first calculate its monthly index as the maximum of the daily index over a given month across all monitoring stations located within a five-mile radius of a mutual fund's location and then compute the average of the monthly index over a quarter.	EPA's Air Quality System (AQS) database https://aqs.epa.gov/aqsweb/airdata/download_files.html#Daily
Emissions	The natural logarithm of the sum of firm *i*'s total carbon emissions of all three scopes (i.e., Carbon Scopes 1, 2, and 3).	Trucost
TSun	The natural logarithm of 1 plus the average daily sunshine time (in minutes) over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location.	National Climatic Data Center (NCDC)
Wind	The natural logarithm of 1 plus the daily average wind speed over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location.	NCDC
Tmp	The average of daily temperatures over a quarter across monitoring stations located within a five-mile radius of a mutual fund's location. Following the literature, the average temperature in a given day is the average of the maximum temperature and the minimum temperature within the day.	NCDC
Ln(Fund Size)	The natural logarithm of total net assets (TNA). For funds with multiple share classes, *Fund Size* is the total net assets of all share classes.	CRSP Mutual Funds, Thomson Reuters Mutual fund holdings (s12)
Exp Ratio	A fund's expense ratio as reported in the CRSP Mutual Funds database. For funds with multiple share classes, *Exp Ratio* is the weighted average of the expense ratio using individual share classes' total net assets as the weight.	CRSP Mutual Funds

Turn Ratio	A fund's turnover ratio as reported in the CRSP Mutual Funds database. For funds with multiple share classes, *Turn Ratio* is the weighted average of the turnover ratio using individual share classes' total net assets as the weight.	CRSP Mutual Funds
Fund Ret	Average monthly returns over a quarter. For funds with multiple share classes, fund returns are computed as the weighted average of returns using individual share classes' total net assets as the weight.	CRSP Mutual Funds
Fund Flow	Fund flow over the period *t*-1 to *t* is computed as $[TNA_t - (1 + Fund\ Ret_t)TNA_{t-1}]/TNA_{t-1}$.	CRSP Mutual Funds
Size	The natural logarithm of market capitalization. Market capitalization is calculated as a stock price (*PRCC_F*) multiplied by the number of shares outstanding (*CSHO*).	Compustat
Ln(BM)	The natural logarithm of 1 plus the book-to-market ratio. The book-to-market ratio is calculated as the book value of equity (*CEQ*) divided by market capitalization.	Compustat
Momentum	Continuously compounded stock returns over the previous year.	CRSP
Return on Asset	Operating income before depreciation (*OIBDP*) divided by the book value of total assets (*AT*).	Compustat
Sales Growth	The difference between firm-level sales (*SALE*) in the current year and the sales in the previous year divided by sales in the previous year.	Compustat
Leverage	The sum of long-term debt (*DLTT*) and debt in current liabilities (*DLC*) divided by the market value of assets, where the market value of assets is computed as total assets (*AT*) minus the book value of equity (*CEQ*) plus market capitalization.	Compustat

Appendix Table A2: Industry-Adjusted Carbon Emissions

Panel A reports the results of regressions with the industry-adjusted measure of carbon emissions. We repeat the regression associated with Column 1 of Table 2 Panel A but replace the *Emissions* measure with an industry-adjusted measure of carbon emissions, *Emissions Adj*. *Emissions Adj* is calculated as firm-level *Emissions* minus the industry average of *Emissions*, using the Fama and French 48 Industry Classification. Panel B reports the regression results for the sample that removes prominent polluting industries, i.e., oil & gas, utilities, and motor (Bolton and Kacperczyk, 2021). Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Interpretation: Panel A shows that the effects of local air pollution on fund managers' divestment of carbon emitting firms remain robust when we use industry-adjusted *Emissions.* Panel B confirms the robustness of our results when we remove prominent polluting industries. These results also suggest that our findings are not driven by the well-known exclusionary screening criteria based on a few salient industries documented in the literature.

Panel A: Industry-Adjusted Carbon Emissions

	Dependent Variable: $Weight_{t+1}$	
Variable	(1)	(2)
$Emissions\ Adj_t \times AQI_t$	-0.015***	-0.014***
	(-4.353)	(-2.801)
AQI_t	0.199***	0.152**
	(4.340)	(2.431)
$Emissions\ Adj_t$	0.092***	0.135***
	(31.141)	(33.234)
Other Control Variables	Yes	Yes
Fund FEs	Yes	No
Stock FEs	Yes	No
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Fund × Stock FEs	No	Yes
Number of Obs	2,479,757	2,479,757
Adj. R-squared	0.455	0.623

Appendix Table A2: continued

Panel B: Removing Prominent Polluting Industries

	Dependent Variable: $Weight_{t+1}$	
Variable	(1)	(2)
$Emissions_t \times AQI_t$	-0.017***	-0.012**
	(-4.197)	(-2.183)
AQI_t	0.212***	0.122*
	(4.291)	(1.849)
$Emissions_t$	0.107***	0.168***
	(30.509)	(34.695)
Other Control Variables	Yes	Yes
Fund FEs	Yes	No
Stock FEs	Yes	No
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Fund × Stock FEs	No	Yes
Number of Obs	1,860,613	1,860,613
Adj. R-squared	0.456	0.623

Appendix Table A3: Tests Using Change in Carbon Emissions

This table reports the results of regressions with changes in carbon emissions as the main variable. We repeat the regression associated with Column 1 of Table 2 Panel A but replace the *Emissions* measure with the change in carbon emissions, $\Delta Emissions_t$. $\Delta Emissions_t$ is computed as the difference between $Emissions_t$ and $Emissions_{t-1}$ divided by $Emissions_{t-1}$. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Interpretation: The effects of local air pollution on fund managers' divestment of carbon emitting firms remain robust when we use changes in *Emissions* instead of the level of *Emissions*.

	Dependent Variable: $Weight_{t+1}$	
Variable	(1)	(2)
$\Delta Emissions_t \times AQI_t$	-0.108***	-0.091***
	(-5.357)	(-4.054)
AQI_t	0.035	0.012
	(1.636)	(0.594)
$\Delta Emissions_t$	0.052***	0.051***
	(5.284)	(4.784)
Other Control Variables	Yes	Yes
Fund FEs	Yes	No
Stock FEs	Yes	No
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Fund × Stock FEs	No	Yes
Number of Obs	2,178,359	2,178,359
Adj. R-squared	0.461	0.630

Appendix Table A4: State's Political Orientation

This table reports the results of subsample tests based on the political orientations of U.S states. States are classified as Republican or Democratic based on whether they have Republican or Democratic trifecta status. Column 1 reports the results for the subsample of funds located in Democratic states. Column 2 reports the results for the subsample of funds located in Republican states. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Interpretation: The effects of local air pollution on fund managers' divestment of carbon emitting firms is concentrated among those who are located in Democratic states, which tend to adopt stronger pro-environmental attitudes.

	Dependent Variable: $Weight_{t+1}$	
	(1)	(2)
Variable	Democratic	Republican
$Emissions_t \times AQI_t$	-0.016***	-0.009
	(-7.974)	(-1.529)
AQI_t	0.164***	0.293***
	(6.025)	(3.597)
$Emissions_t$	0.094***	0.087***
	(35.289)	(14.621)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	1,479,312	1,000,445
Adj. R-squared	0.471	0.433

Appendix Table A5: Tests Using Firms' Environmental, Social, and Governance Scores
This table reports the results of the regressions with a firm's environmental, social, and governance scores. In Column 1, we repeat the regression associated with Column 1 of Table 2 Panel A but replace the *Emissions* measure with a firm's environmental performance score provided by Sustainalytics, *EScore*. In Column 2, we repeat the regression associated with Column 1 of Table 2 Panel A but replace the *Emissions* measure with the sum of a firm's social and governance scores provided by Sustainalytics, *S&G Score*. Standard errors are clustered at the fund-year-quarter level. *t*-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Interpretation: The effects of local air pollution are strong when we use firm-level environmental scores (*EScore)* as an alternative measure of a firm's environment performance (Column 1). The effects are insignificant, however, for social and governance performance (Column 2), suggesting the unique effects of local air pollution on managers' awareness of climate risk rather than other social responsibility aspects of a firm.

	Dependent Variable: $Weight_{t+1}$	
Variable	(1)	(2)
$EScore_t \times AQI_t$	0.024***	
	(3.757)	
$EScore_t$	-0.016***	
	(-4.938)	
$S\&G\ Score_t \times AQI_t$		0.011
		(0.886)
$S\&G\ Score_t$		-0.009
		(-1.632)
AQI_t	0.002	-0.014
	(0.308)	(-0.525)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	2,677,610	2,677,610
Adj. R-squared	0.507	0.508

Appendix Table A6: Subsample Tests Based on Paris Agreement in 2015

This table reports the results of subsample tests based on the 2015 Paris Agreement. Column 1 reports the regression results for the subsample before the Paris Agreement, i.e., sample period from 2005 to 2015. Column 2 reports the regression results for the subsample following the Paris Agreement, i.e., for a sample period spanning 2016 through 2018. Standard errors are clustered at the fund-year-quarter level. t-statistics are presented in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The variables are defined in Appendix Table A1.

Interpretation: The effects of local air pollution on fund managers' divestment of carbon-emitting firms are equally strong in the periods before and after 2015, suggesting that our results are not driven by general awareness of climate risk caused by the Paris Agreement, as documented in the literature.

	Dependent Variable: $Weight_{t+1}$	
	(1)	(2)
	Before Paris Agreement	After Paris Agreement
Variable	2005-2015	2016-2018
$Emissions_t \times AQI_t$	-0.014***	-0.016***
	(-3.135)	(-2.909)
AQI_t	0.178***	0.206***
	(2.932)	(3.089)
$Emissions_t$	0.087***	0.055***
	(24.267)	(5.889)
Other Control Variables	Yes	Yes
Fund FEs	Yes	Yes
Stock FEs	Yes	Yes
Fund County FEs	Yes	Yes
Year-Quarter FEs	Yes	Yes
Number of Obs	1,758,512	721,245
Adj. R-squared	0.439	0.552