Pollution Premium: Further Evidence

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Abstract

This paper presents novel empirical evidence related to the pollution premium. First, investors are concerned about whether a firm has higher scaled emissions relative to its industry peers rather than companies in other sectors. Second, it is the emission intensity but not the level of or growth rate in total emissions that is priced in the cross-section. Third, the positive relation between emission intensity and future returns in a multivariate setting is dependent on the inclusion of industry-fixed effects. Fourth, variables that proxy for limits-to-arbitrage and informational frictions do not account for the pollution premium. Fifth, there is no indication that firms with higher scaled emissions produce higher earnings surprises which does not support a mispricing-based explanation. Finally, firms with higher emission intensities have lower institutional ownership by investment advisers.

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1. Introduction

Asset pricing implications of corporate social responsibility (CSR), climate change and firms' environmental, social and governance (ESG) performances constitute a rapidly growing body of literature. Some studies find that firms with higher social capital and better engagement with ESG issues are less risky (Lins et al., 2017; Albuquerque et al., 2019; Hoepner et al., 2024). Studies that focus on carbon emissions find that polluting firms carry higher risk exposures (Ilhan et al., 2021; Barnett, 2023; Bolton and Kacperczyk, 2021, 2023). Behavioral phenomena such as under- or overreaction to environmental news, investor inattention and social sentiment can also drive return predictability (Kruger, 2015; Hong et al., 2019; Chen et al., 2020; Atilgan et al., 2024). Many investors have a preference towards stocks with better CSR and ESG scores[1] which can further affect asset prices and systematic risk exposure (Pastor and Stambaugh, 2021, 2022; Ardia et al., 2023). Another group of studies finds that firms with environmental issues face higher costs of capital (Heinkel et al., 2001; Hong et al., 2023; de Angelis et al., 2023).

Hsu et al. (2023) make a significant contribution to this literature by investigating how industrial pollution is priced in the cross-section of stock returns. They use facility-level data on toxic pollutant emissions to generate a measure of emission intensity (total emissions scaled by firm size) at the firm-level. Their main finding is that firms producing more scaled emissions are associated with higher subsequent returns after controlling for various asset pricing factors and firm characteristics. The authors consider several explanations for the pollution premium. First, the premium may be compensation for various systematic risks attached to companies with higher scaled emissions. These risks may be driven by technology obsolescence (Lin et al., 2019), financial constraints (Li, 2011), political and economic uncertainty (Bali et al., 2017; Brogaard and Detzel, 2015), and adjustment costs (Gu et al., 2018). Second, high-emission intensity firms could be operating under weaker governance, or they may be more politically connected such that their profits are subject to more uncertainty with respect to governance. Third, behavioral issues may be at play such as both retail and institutional investors having preferences against firms with a poor social image, or retail investors overreacting to firms' emission news. However, bivariate

[1] See Renneboog et al. (2008), Riedl and Smeets (2017), Dyck et al. (2019), Hatzmark and Sussman (2019), Krueger et al. (2020), Liang et al. (2022), Hwang et al. (2022), Ilhan et al. (2023), and Cao et al. (2023) for institutional investors' preferences towards sustainable investment. Bauer at al. (2021) and Heeb et al. (2023) conduct field experiments to investigate individuals' preferences.

sorts and multivariate regressions indicate that none of these explanations can account for the pollution premium.

Next, the authors develop a model based on environmental policy uncertainty where firms' cash flows are sensitive changes in environmental regulations. In the model, the government optimally replaces a weak-regulation regime with a strong-regulation regime if the negative externality induced by toxic emissions is sufficiently high, and firms are able to estimate a perceived probability of regime shift by observing signals. If a strong-regulation regime is adopted, firms with high emission intensities are affected more adversely since the higher sensitivity of their profits to regime shift is coupled by an overall jump in the stochastic discount factor. This type of systematic risk can explain the higher expected returns to firms with higher scaled emissions. The study also tests this model by using the growth rate in the aggregate amount of pollution-related civil penalties as a measure of regime change risk. This risk is negatively priced in the cross-section with higher emission-intensity firms possessing lower betas. Moreover, environmental policy uncertainty is distinct from general policy uncertainty that has been investigated by prior literature (Bloom, 2009).

In this paper, our first goal is to investigate how some methodological choices made by Hsu et al. (2023) impact the existence or magnitude of the pollution premium. We aim to gain a deeper understanding of investor preferences towards industrial pollution rather than discrediting prior findings. Hsu et al. (2023) assign firms into portfolios based on their scaled emissions relative to industry peers due to the fact that toxic emissions tend to vary across business sectors. Thus, the documented pollution premium indicates that investors impose a higher return premium to firms with higher emission intensity compared to other firms in the same industry. We first confirm the original findings in an updated sample period. We later examine whether investors demand a higher premium from high-emission intensity stocks regardless of industry designation. In other words, we ask the question whether investors also penalize the entire set of companies that operate in industries that generate more scaled emissions. To answer this question, we repeat the portfolio analyses in Hsu et al. (2023) without initial industry sorts and find that pollution premium is solely an intra-industry phenomenon. Third, motivated by the debate in the literature regarding the relation between carbon emissions and stock returns, we examine which measures of toxic emissions are priced by investors. Specifically, we ask the question whether investors are only concerned about emissions scaled by a proxy for firm size, or they also penalize companies that emit more toxic pollutants regardless of their size. We find that it is only emission intensity that is priced since portfolio sorts based on the level of or growth in emissions produce no pollution premia. Fourth, we conjecture that regime change risk related to environmental policies could be a more pronounced factor in recent years as investors became more aware and vocal about environmental concerns. However, there is no robust evidence that the pollution premium is stronger in the second half of our sample period. Fifth, we find that high versus low emission intensity firms display significant dispersion in terms of a number of firm characteristics that have been shown by prior asset pricing studies to influence the cross-section of equity returns. Controlling for many of these control variables in bivariate sorts renders the pollution premium insignificant, however, these sorts may lack power due to within-industry sorting. When we control for these characteristics in multivariate cross-sectional regressions, emission intensity does have a significantly positive relation with future returns, but only after including industry fixed-effects in the specifications. Since these fixed-effects correspond to demeaning all variables at the industry level, it would be more accurate to state that firms with higher scaled emissions *relative to their industry peers* earn higher future returns *relative to their industry peers*.

Our second goal in this paper is to test for some alternative explanations of the pollution premium that have not been entertained by Hsu et al. (2023). First, we rely on the anomalies literature to test whether the pollution premium can be accounted for limits-to-arbitrage, mispricing or informational frictions. Specifically, we utilize bivariate sorts on emission intensity and a number of variables that capture how exposed stocks are to costly arbitrage, mispricing and informational uncertainty. We find no evidence that the pollution premium is concentrated among more mispriced stocks that are costlier to arbitrage and subject to more informational frictions. Second, to further inquire into a mispricing-based story, we examine whether higher returns to firms with higher emission intensities are concentrated around earnings announcements. It may be the case that investors initially underprice firms with higher scaled emissions, but then reward them with higher returns as companies post higher unexpected earnings due to lack of emission abatement in the presence of delayed regulation. We find no evidence for this hypothesis since there is no significant relation between emission intensity and different measures of standardized unexpected earnings. Third, we consider a divestment-based hypothesis for the pollution premium. If a sufficient proportion of institutional investors divest from stocks of firms with higher scaled emissions, the ensuing demand pressure could push the prices of such stocks downwards compared to their expected cash flows. We test this conjecture by looking at the relation between emission intensity and ownership ratio attached to various groups of institutional investors. Although we find that investment companies such as mutual funds have reduced holdings in high emission-intensity firms, the economic magnitude of this effect is limited.

The rest of the paper is organized as follows. Section 2 describes data sources and variable definitions. Section 3 presents empirical results. Section 4 concludes.

2. Data and Variables

2.1 Data sources

We obtain plant-level chemical pollutants data from the Toxic Release Inventory (TRI) database maintained by the Environmental Protection Agency (EPA).[2] The database was constructed in 1986 in response to public concerns over the release of toxic chemicals from various environmental incidents. EPA tracks certain classifications of toxic substances and chemical pollutants that cause adverse health and environmental effects.[3] It further mandates every facility that falls within a TRI-reportable sector, has ten or more employees, and crosses a certain threshold in manufactured or processed TRI-listed chemicals to report the amount of each chemical being released.[4,5] The database contains reporting years, chemical categories, chemical pollutant levels, facility locations and parent company names. TRI has an exceedingly high ratio of zeros in facilities' chemical emissions before 1991, thus, we utilize facility-level TRI data from 1991 to 2022. For each facility in a year, we use the value of the item "PRODUCTION WSTE (8.1-8.7)" which is the sum of the amounts of all toxic emissions in pounds across all chemical categories. Then, we aggregate annual facility-level total emissions by parent names to estimate firm-level total emissions.

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[2] See Chava (2014), Currie et al. (2015), Kim et al. (2019), Akey and Appel (2021), Xu and Kim (2022), Heath et al. (2023), and Jing et al. (2023) for other studies that utilize this database.

[3] The current TRI toxic chemical list contains over 600 individually listed chemicals that correspond to a multitude of environmental categories, including air pollution, clean energy, acid rain, hazardous waste and safe drinking water.

[4] It is a criminal offense to falsify information given to the U.S. government. There are also civil and administrative penalties for non-compliance with TRI reporting mandates. Moreover, EPA monitors each form submitted by a facility for potential errors, conducts an extensive quality analysis of the reported data and provides analytical support for enforcement efforts led by its Office of Enforcement and Compliance Assurance.

[5] The mandatory nature of this reporting makes it less likely for firms to self-select themselves into disclosure or non-disclosure. This minimizes the likelihood of endogeneity which is a more serious issue in studies focusing on the effects of carbon emissions on stock returns in which case disclosure is voluntary.

Stock return and accounting data come from CRSP and Compustat, respectively. Institutional holdings data are retrieved from Thomson Reuters Institutional Holding (13F) database. Analyst forecast estimates are obtained from I/B/E/S. One challenge in using TRI data is the lack of linking keys with various financial databases. Thus, we follow Hsu et al. (2023) and use a string-matching algorithm to match parent names in the TRI database to the names of U.S. public companies in CRSP and Compustat. Specifically, we remove all punctuation marks, clean special characters and standardize most common words to a consistent format.[6] We keep all unique matches with similarity scores equal to 100%. When there are multiple matches and similarity scores are below 100%, we rank all potential matches based on their scores and manually identify the appropriate matches. We include all domestic common shares trading on NYSE, AMEX or Nasdaq with non-missing TRI data and SIC codes. We exclude financial firms and require that firms are listed on Compustat for at least two years before being included in the sample.[7] The final sample used in the portfolio analyses consists of 111,753 firm-month observations.

2.2 Variable definitions

It is possible that any significant relation between emission intensity and future returns is driven by a correlation between emission intensity and some firm characteristic that has been established to be a significant determinant of the cross-section of equity returns by the prior literature. Thus, we control for various stock attributes in bivariate portfolio and Fama and Macbeth (1973) cross-sectional regression analyses. *Beta* is the market beta with respect to the CRSP value-weighted market index calculated from daily returns during the past year.[8] Following Fama and French (1992), we calculate the natural logarithm of market capitalization in millions of dollars (*Size*) and book-to-market equity ratio (*BM*) where book value of equity is measured at the fiscal year end in calendar year *t*-1. We control for the short-term reversal (*STR*) effect of Jegadeesh (1990) and the momentum (*MOM*) effect of Jegadeesh and Titman (1993) using the one-month lagged stock return and cumulative return during the past 12 months

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[6] For example, we standardize "Manufacturing" to "MFG", "Internationals" to "INTL", "Incorporation" to "INC", "Company" to "COM", "Industry" to "IND", etc.

[7] We use two extra screens that are not discussed in Hsu et al. (2023) but are included in their replication code. First, we drop industries with less than 20 firms in a year based on the Fama and French (1997) 49-industry classification. As a result, sample firms come from 18 distinct industries which are identical to those listed in Table A8 of Hsu et al. (2023). Second, we drop an observation if total assets or sales are less than one million dollars.

[8] We require that at least 150 (10) non-missing daily return observations exist in a year (month) when we calculate variables using within-year (month) data.

skipping the most recent month, respectively. To account for the illiquidity premium, we calculate the Amihud (2002) illiquidity measure (*Illiq*) as the absolute daily return of a stock divided by its daily dollar trading volume (in millions) averaged over the month. Coskewness (*Coskew*) is calculated as the coefficient of the squared excess market return term from a regression of daily excess stock returns on daily excess market returns and squared daily excess market returns in the past year following Harvey and Siddique (2000). Following Ang et al. (2006), we calculate idiosyncratic volatility (*IVOL*) as the standard deviation of error terms from the application of the three-factor model of Fama and French (1993) to daily excess stock returns within a month. Following Bali et al. (2011), we take the lottery-demand effect into account by calculating the average of the five highest daily returns of each stock (*MAX*) in each month. Finally, to control for the cross-sectional pricing effects of profitability (Novy-Marx, 2013) and investment (Cooper et al., 2008), we calculate operating profitability (*OP*) as earnings before interest and taxes scaled by shareholders' equity for the most recent quarter prior to the portfolio formation month and asset growth (*IA*) as the annual percentage change in total assets for the fiscal year ending in calendar year t-1, respectively.[9]

To test whether costly arbitrage provides an explanation for the pollution premium, we investigate the interactions between emission intensity and firm size, illiquidity and firm age (*AGE*) defined as the number of months that a stock has been listed on the CRSP database. To examine whether informational frictions can account for the pollution premium, we use institutional ownership ratio (*INST*) calculated by dividing the institutional ownership level computed using equity holdings by institutions that file 13F reports by total shares outstanding at the latest quarter end. We further use analyst coverage (*CVRG*) defined as the number of analysts covering the stock in the I/B/E/S database and firm size as alternative proxies for information frictions. Finally, to investigate whether the pollution premium is stronger among stocks that are more mispriced, we use the mispricing metric (*MISP*) of Stambaugh et al. (2017). This measure is created by ranking stocks independently based on 11 return anomalies in such

[9] This list of control variables has firm size, book-to-market ratio, operating profitability and investment in common with that used by Hsu et al. (2023) although we measure the latter two in an alternative way. The other characteristics controlled by Hsu et al. (2023) are tangibility, financial constraints, operating leverage and book leverage which are borrowed from the corporate finance literature and not commonly used by cross-sectional asset pricing studies.

an order that a higher rank is associated with lower one-month-ahead stock returns.[10] Next, the arithmetic average of the ranks of the 11 anomalies (with a minimum of five available) is taken.

The pollution premium can also be due to institutional investors divesting from stocks of companies that emit relatively more toxic pollutants. To test this hypothesis, we regress institutional ownership ratio (*INST*) as defined above on emission intensity and various control variables. We further decompose institutional ownership with respect to subgroups of owners. *INST_BANK* is ownership ratio by banks, *INST_INSUR* is ownership ratio by insurance companies, *INST_INVEST* is ownership ratio by investment companies (such as mutual funds), *INST_ADVISER* is ownership ratio by independent investment advisers (such as investment banks, brokers, private wealth management companies) and *INST_OTHER* is ownership ratio by other institutions (such as pension funds, sovereign wealth funds, hedge funds).

In our final set of tests, we investigate the relation between toxic emission intensity and earnings surprises. *SUE1* is the one-year earnings surprise calculated as the actual earnings per share (EPS) for the fiscal year ending in year *t* minus the median analyst forecast, scaled by the year-end stock price. The analyst consensus forecast is taken eight months prior to the end of the forecast period, i.e. four months after the prior fiscal year-end, to ensure that analysts observe prior earnings when making their forecasts. *SUE2* is the two-year earnings surprise and calculated in an analogous manner, with the consensus forecast taken 20 months prior to the end of the forecast period. As in Easterwood and Nutt (1999), Giroud and Mueller (2011), and Edmans (2011), we remove observations where the forecast error is larger than 10% of the stock price. *LTG* is the long-term growth surprise and equal to the actual five-year EPS growth taken from I/B/E/S minus the median growth forecast from 56 months earlier.

3. Empirical results

3.1 Univariate portfolio sorts

In our baseline univariate portfolio analyses, we scale total emissions (in pounds) in year *t*-1 by total assets, plant, property and equipment, sales or market value of equity disclosed by the end of March of year *t*. Emissions data for year *t*-1 are updated between July and September of

[10] These anomalies are financial distress, O-score bankruptcy probability, net stock issues, composite equity issues, total accruals, net operating assets, momentum, gross profitability, asset growth, return on asset, and investment-to-assets.

year t in TRI, thus, we construct portfolios at the end of September of year t to avoid look-ahead bias. We sort all firms with positive emission intensities in year t-1 into quintiles within 49 Fama and French (1997) industries.[11] We calculate monthly value- or equal-weighted excess returns of these quintiles from October of year t to September of year t+1. Next, we form an arbitrage portfolio that takes a long (short) position in stocks in the high-emission (low-emission) intensity quintile. We also calculate two measures of abnormal returns (alphas) as intercept terms from time-series regressions of emission intensity-sorted portfolios' excess returns on two sets of asset pricing factors. FF6PS model augments the market, size, value, profitability and investment factors of Fama and French (2015) by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS model augments the market, size, profitability, investment and expected growth factors of Hou et al. (2021) by the liquidity factor of Pastor and Stambaugh (2003).[12] We multiply all excess returns and alphas by 12 and report annualized average returns in percentage. Moreover, all t-statistics are based on standard errors that are corrected for heteroskedasticity and autocorrelation using the Newey and West (1987) procedure with 12 lags.

Results are presented in Table 1. When emissions are scaled by total assets in Panel A, the annualized value-weighted excess return spread between extreme quintiles is 6.13% (t-statistic = 2.64). FF6PS and Q5PS alphas associated with the arbitrage portfolio are also significantly positive with values of 3.47% and 5.91%, respectively. When the scaling variable is altered to plant, property and equipment, total sales and market value of equity in Panels B to D, all value-weighted return spreads remain significantly positive with values of 4.80%, 6.00% and 4.61%, respectively. Moreover, five of the six alphas are also statistically significant at least at the 10% level. Similar findings are observed for equal-weighted portfolio returns in the right-hand side of Table 1.[13] These findings reaffirm the existence of the pollution premium in an extended sample period.[14]

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[11] Findings are robust to using GICS industry or 2-digit SIC codes.

[12] Risk-free rates and factor data for the FF6 model are obtained from Kenneth R. French's website. Factor data for the Q5 model are obtained from global-q.org. Liquidity factor data are obtained from Robert Stambaugh's website. Hsu et al. (2023) report alphas based on CAPM, FF3, FF4, FF5 and Q4 models neither of which adjust for the expected growth and liquidity factors.

[13] Many anomalies have been shown to be more pronounced among smaller stocks that are exposed to higher arbitrage costs and informational frictions. When we compare the economic magnitude of the pollution premium based on value- versus equal-weighted returns, we do not observe a consistent pattern. Value-weighted return spreads between extreme quintiles are higher for three scaling variables (except market value of equity) and value-weighted alpha spreads are higher for four out of eight metrics. However, returns and alphas associated with the arbitrage portfolio are all statistically more significant for equal-weighted portfolio returns with t-statistics never dipping below 3.

[14] Portfolios are updated annually, thus, emission intensity observed in September of year t is used to forecast 12 different monthly returns from October of year t to September of year t+1. Our baseline tests correspond to the average

As explained above, baseline portfolio sorts are conducted within industries following Hsu et al. (2023). In other words, firms are classified to have high or low emission intensities based on how much their scaled emissions are on a relative basis with respect to companies in the same sector. Thus, the findings of Table 1 indicate that investors demand a higher return premium from stocks of firms that pollute more relative to their industry peers. This raises the question whether investors also price scaled emissions at an absolute basis in the cross-section. Some industries in our sample, such as medical equipment and lab equipment, have substantially lower average emission intensities compared to other industries such as oil and construction. It is possible that a company that is placed in the lowest emission intensity quintile in the oil industry would have found itself in the highest emission intensity quintile if it was operating in the medical equipment industry. To answer this question, we conduct univariate sorts across industries such that companies that operate in inherently high-scaled emission (low-scaled emission) industries are represented at a higher frequency in the high-emission intensity (low-emission intensity) quintile.

Results are presented in Table 2. Value-weighted returns to the arbitrage portfolio that is long (short) in stocks with high (low) emission intensity are smaller in magnitude compared to the analogous figures in Table 1. Moreover, value-weighted return spreads become statistically insignificant at the 5% level when the scaling variable is assets or sales. Furthermore, none of the associated alphas are statistically significant at the 5% level. Equal-weighted returns to the arbitrage portfolio tell a similar story with no evidence for a pollution premium with the exception of market value of equity as the scaling variable.[15]

These findings indicate that investors are concerned about where companies stand among their industry peers with respect to their emission intensities, however, they do not demand a return premium from stocks of companies which do not pollute relatively more with respect to their industry peers even if they pollute relatively more with respect to the overall universe of equities. In other words, investors do not penalize entire industries when they price industrial pollution in the cross-section.[16]

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predictive power of emission intensity for these 12 distinct monthly returns. When we investigate the relation between emission intensity and monthly returns from one- to twelve-months ahead separately, we find that the predictive power of emission intensity becomes statistically insignificant after six months.

[15] We also conduct an additional test where we de-mean scaled emissions of a firm with the average scaled emissions of its industry and sort stocks into quintiles based on these demeaned emission intensities across industries. Equal-weighting still produces a significant pollution premium for all scaling variables, however, value-weighted return spreads become statistically insignificant when total assets or market value of equity is used to scale total emissions.

[16] All portfolio sorts are done within industries from this point on in the paper.

3.2 Level of and growth in emissions

The correct measure of emissions has been a contentious subject of debate in the literature that investigates the relation between carbon emissions and equity returns. Bolton and Kacperczyk (2021) find that stocks of firms with higher total carbon dioxide emissions and changes in emissions earn higher returns, however, a similar relation is not observed for emission intensity which is defined as tons of CO_2 equivalent divided by total revenues. Aswani et al. (2024a) point out that a key component that data vendors use to estimate carbon emissions is firm size, thus, measuring emissions in terms of intensity, rather than its raw value, is more effective in neutralizing any mechanical correlation with firm size. Bolton and Kacperczyk (2024) respond to this critique by making the point that a large firm can be perceived as more environmentally friendly than a small firm, even though its impact on the climate in terms of the magnitude of its carbon emissions is much larger. They also argue that dividing emission levels by revenues introduces noise to the proxy for carbon transition risk exposure because changes in emission intensity can be due to either changes in total emissions or changes in revenues. Aswani et al. (2024b) reply to this rebuttal by stating that, if consumers demand a certain quantity of a good, it is overall greener for the economy if firms with lower emission intensity produce more of the good. Thus, if firms are not going to cut down economy-wide production, then total emissions are not an appropriate measure of firm-level carbon risk. Moreover, after acknowledging that scaling emissions by revenues introduces noise, they argue that this is still less problematic than including both total emissions and a proxy for firm size as two separate independent variables since this introduces severe multicollinearity to regression specifications.

We do not to pick a side on this argument, and we already know that, contrary to carbon emission intensity, toxic emission intensity is priced in the cross-section of equity returns. Still, we would like to know whether investors also demand a higher return premium for stocks of firms that emit a higher level of toxic pollutants or experience a higher growth in the amount of total emissions. To answer this question, we repeat the within-industry univariate sorts of Table 1, however, we use the level of raw emissions or the annual percentage growth rate in raw emissions as sorting variables rather than emission intensity. Results are presented in Table 3. Panel A shows that the value- and equal-weighted return and alpha spreads between extreme raw emission quintiles are all statistically indistinguishable from zero. Panel B shows that the annualized value-weighted return spread between the highest and lowest emission growth quintiles is 6.02% with a *t*-statistic of 1.72, however, FF6PS and Q5PS alphas are statistically insignificant. Equal-weighted return and alpha spreads based on emission growth sorts are also statistically insignificant.[17] These results suggest that, unlike the carbon premium, investors demand a pollution premium based on the magnitude of toxic emissions relative to firm size rather than the level of or growth in these emissions.

3.3 Subperiod analysis

The Paris Agreement, that was negotiated during the United Nations Climate Change Conference in December 2015, raised awareness of risks tied to carbon emissions at a global scale. With 195 signatories committing to limit the rise in global surface temperature to well below 2 °C (3.6 °F) above pre-industrial levels, the agreement also increased the prospect of regulatory interventions to limit carbon emissions. As a result, many researchers were motivated to investigate how investors reacted to the agreement (e.g., Monasterolo and de Angelis, 2020; Alessi et al., 2024). In particular, Bolton and Kacperczyk (2021, 2023) find that the global carbon premium jumps after the Paris agreement and becomes highly significant.

When it comes down to industrial pollution, there are no landmark regulatory events in our sample period that had as major a global impact as the Paris Agreement. Moreover, despite several United Nations summits (such as the ones held in Stockholm and Rio de Janeiro in 1972 and 1992, respectively) which aimed to develop an international environmental law, most legislation related to pollution are effective at the national or local level and date back to several decades ago.[18] Nonetheless, it would not be a stretch to state that environmental problems have become more pronounced and visible in recent periods and the corporate world has become more sensitive towards these issues under practices labelled as corporate social responsibility, sustainable business or "ESG". The finance industry has also become more engaged with environmental issues as institutional investors have made the environmental performances of

[17] We only report value-weighted portfolio returns from this point on in the paper since conclusions are qualitatively the same for equal-weighted returns.

[18] Some examples from the United States include Clean Air Act of 1963 (amended several times until 1990), Clean Water Act of 1972 (amended in 1977 and 1987), Safe Drinking Water Act of 1974 (amended in 1986 and 1996), Solid Waste Disposal Act of 1965 and Resource Conservation and Recovery Act of 1976 (amended in 1984 and 1996), Toxic Substances Control Act of 1976, Oil Pollution Act of 1990.

firms a key factor in their portfolio allocation decisions. As a result, the regime change risk that has been identified by Hsu et al. (2023) is likely to be more relevant later in our sample period.

We test whether periods with greater environmental awareness are associated with a higher pollution premium by conducting the univariate sorts of Table 1 separately for two subperiods that range from 1992 to 2006 and 2007 to 2022. In Panel A of Table 4, when the scaling variable is total assets, one can see that the return spread between high- and low-emission intensity quintiles during the first subsample is 3.75% with FF6PS and Q5PS alphas equal to 2.30% and 3.47%, respectively. Analogous figures in the second subsample are 8.31%, 5.21% and 8.88% which indicates that the economic magnitude of the pollution premium has more than doubled over time. Return and alpha spreads between extreme emission intensity quintiles are also higher in the second subsample in Panel C where the scaling variable is total sales. However, these patterns are reversed in Panels B and D where raw emissions are scaled by plant, property and equipment, and market value of equity, respectively. For example, in Panel B, the return, FF6PS alpha and Q5PS alpha to the arbitrage portfolio are 5.37%, 3.66% and 5.04% in the first subsample, respectively, whereas the analogous figures are 4.27%, 2.63%, 3.37% in the second subsample. Furthermore, in these two panels, the pollution premium does not exhibit any statistical significance during the second subsample. To summarize, whether the pollution premium became more pronounced over time as investor and corporate awareness heightened about environmental issues is dependent on how emission intensity is empirically defined.[19]

3.4 Portfolio characteristics

Having identified a significant return difference between firms that have higher and lower scaled emissions with respect to their industry peers, we also want to understand what type of firm characteristics are associated with the highest and lowest polluters. This is important because if emission intensity is positively correlated with some characteristics that have a positive relation with subsequent returns, it is possible that the pollution premium is simply capturing an already established anomaly. On the other hand, if emission intensity is negatively correlated with some characteristics that have a positive relation with subsequent returns, it may be the case that an already established anomaly is partially subsuming the pollution premium.

[19] After this point in the paper, we scale total toxic emissions by total assets to calculate emission intensity. Results for all subsequent analyses are qualitatively robust for the other scaling variables.

Table 5 demonstrates that there are significant differences in several firm characteristics between high- versus low-emission intensity quintiles. In particular, compared to stocks with low scaled emissions, high-emission intensity stocks have higher past month returns, momentum, idiosyncratic volatility and lottery-like payoffs, and lower market capitalizations, book-to-market ratios and liquidity. Prior literature finds that these firm characteristics are instrumental in determining the cross-section of expected equity returns. Specifically, smaller and less liquid firms with higher momentum returns tend to have higher future returns, hence, it is possible that these return predictors drive the pollution premium. On the other hand, growth firms with higher past one month returns, idiosyncratic volatility and lottery demands tend to have lower future returns, hence, these return predictors may be masking the strength of the positive relation between emission intensity and future returns. Thus, in the subsequent two sections, we control for these return predictors via bivariate sorts and multivariate Fama-Macbeth regressions.

3.5 Bivariate portfolio sorts

In the bivariate portfolio analyses, we sort stocks into two groups based on the median value for each control variable within each industry-month. Next, each of these two groups is sorted into quintiles based on emission intensity to generate 2x5 portfolios within each industry. Subsequently, we aggregate the emission intensity-sorted portfolios across industries and control variable groups to obtain portfolios that display dispersion in emission intensity but are similar in terms of other firm characteristics. In addition, we again form an arbitrage portfolio that is long in the resulting high-emission intensity portfolio and short in the resulting low-emission intensity portfolio.

Table 6 presents annualized FF6PS and Q5PS alphas for the return difference between the high- and low-emission intensity portfolios obtained after dependent bivariate sorts. One can observe that, after controlling for most of the firm characteristics, abnormal returns to the arbitrage portfolio become statistically insignificant. In fact, for Q5PS alphas, the arbitrage portfolio generates significantly positive abnormal returns (at the 10% level) after controlling for market beta, coskewness, idiosyncratic volatility and operating profit. For all other firm characteristics, the alpha spread between extreme emission intensity quintiles is statistically indistinguishable from zero. However, we would like to advise the reader to interpret these findings with caution. Our bivariate sorts can be interpreted as trivariate sorts (just as earlier univariate sorts can be interpreted as bivariate sorts) since the initial sorting is done based on industries. As a result, each of the 2x5 portfolios within each industry individually are not as diversified and well-populated as the ones that would have been obtained without initial industry sorting. Therefore, the loss of predictive power of emission intensity for future equity returns can be due to the reduced power of bivariate sorts conducted within industries.

3.6 Cross-sectional regressions

Portfolio analyses suffer from the aggregation effect due to suppressing individual firm-level information in the cross-section and cannot control for the potential impact of multiple firm characteristics simultaneously. To mitigate these problems, we run Fama-MacBeth regressions at the stock level by regressing annualized monthly stock returns from October of year *t* to September of year *t*+1 on emission intensity in natural logarithm of year *t*-1 (which is reported in September of year *t*) and different sets of control variables. Table 7 presents the time-series average of the monthly slope coefficients.

The left-hand side of Table 7 also includes industry fixed-effects in the specifications following Hsu et al. (2023). In the univariate specification, emission intensity has a slope coefficient of 0.550 with a *t*-statistic of 3.56. Next, we add market beta and one-month-lagged return to the specification and emission intensity continues to have a positive relation with future returns with a slope coefficient of 0.560 and a *t*-statistic of 3.60. Adding more firm characteristics among the independent variables reduces the slope coefficient of emission intensity, but it is still highly significant in the full specification with a slope coefficient of 0.427 and a *t*-statistic of 2.79.[20]

One lingering issue is the usage of industry fixed-effects in the estimations. Aswani et al. (2024a) find that, in the U.S., there is a significantly positive relation between the level of carbon emissions and future equity returns only if industry fixed-effects are included. Moreover, even the choice of industry definitions used to implement industry fixed-effects has a material impact on findings. Furthermore, in Europe, carbon emission intensity can positively predict future returns, but this time, only in the absence of industry fixed-effects. Although the authors do not

[20] We estimate these regressions by adding one control variable at a time, however, only report results from selected specifications to conserve space. Emission intensity always has a significantly positive coefficient in regressions that incorporate industry fixed-effects.

take a stance on the correct set of fixed effects, these findings highlight the importance of empirical design choice.

An important difference between the econometric specification used in Aswani et al. (2024a) and what we implement following Hsu et al. (2023) is that we estimate Fama-MacBeth cross-sectional regressions rather than panel regressions. The usage of various fixed effects is standard practice in corporate finance studies, but it is uncommon in asset pricing studies that focus on cross-sectional anomalies. Thus, we proceed to re-estimate the prior specifications without industry fixed-effects. The univariate specification in the right-hand side of Table 7 shows that emission intensity continues to have a significantly positive coefficient although its magnitude and statistical significance diminishes. Adding market beta and one-month-lagged return does not neutralize the predictive power of emission intensity, however, including more control variables does. The coefficient of emission intensity is statistically indistinguishable from zero in the last three specifications reported in Table 7. In fact, although unreported, adding only firm size to market beta and one-month-lagged return is sufficient to render the coefficient of emission intensity insignificant. Incorporating industry fixed-effects adjusts for the impact of industry-specific and time-invariant unobservable variables on the regressand. Econometrically, it is equivalent to demeaning each variable at the industry level and estimating the regressions. Thus, multivariate regressions of this section indicate that firms' emission intensities with respect to their industry peers have a significantly positive relation with their future returns with respect to their industry peers, a finding which is reminiscent of the differences between within- and across-industry sorts conducted in Tables 1 and 2.

3.7 Costly arbitrage, informational frictions and mispricing

A positive relation between emission intensity and future returns can also be interpreted in the sense that investors underprice (overprice) equities with higher (lower) emission intensity, and thus, firms with higher (lower) scaled emissions experience abnormally high (low) returns until the mispricing vanishes. The prior literature relies on firm size, illiquidity and firm age to capture arbitrage costs (Shleifer and Vishny, 1997; Amihud, 2002; Stambaugh et al.; 2015). Thus, to test whether limits-to-arbitrage can provide an explanation for the pollution premium, we first sort stocks into two groups within each industry based on *Size*, *Illiq* or *AGE*. Next, we divide each size, illiquidity and age group into quintiles based on emission intensity to generate 2x5 portfolios within each industry. Subsequently, we aggregate across industries to obtain 2x5 portfolios of costly arbitrage and emission intensity for the overall sample. Finally, we calculate the return to the arbitrage portfolio that is long (short) in stocks with high (low) emission intensity for each size, illiquidity and age group. Results are presented in Table 8.[21] We find that the abnormal return difference between the highest and lowest scaled emission quintiles is statistically insignificant within smaller, less liquid and more mature firms. To the contrary, annualized alpha spreads are equal to 6.36%, 6.24% and 10.32% with *t*-statistics of 2.57, 2.55 and 2.13 within larger, more liquid and younger firms, respectively. These findings present a mixed picture since the pollution premium is stronger for larger and more liquid firms that are subject to lower arbitrage costs, but also stronger for younger firms which are subject to higher arbitrage costs. It is also important to highlight that, in all the stock subsamples we have examined up to this point, any observed pollution premium is driven by the short legs of the arbitrage portfolio. Portfolio characteristics as reported in Table 5 suggest that the short leg of the arbitrage portfolio (stocks with lower emission intensity) contain, on average, larger and more liquid stocks. Since short-selling such stocks is relatively easier, limits-to-arbitrage does not seem to have a prominent role in explaining the pollution premium.

Another interpretation of the pollution premium is related to informational frictions. If firms' toxic emissions relative to their industry peers constitute less tangible information compared to those released in well-defined information events such as earnings announcements, investors would have more difficulty in processing this information as argued by Hirshleifer et al. (2013). This would imply that the pollution premium would be more pronounced among stocks with higher information uncertainty. We proxy for such frictions using institutional ownership ratio and repeat the previous bivariate sorts using this ratio as the initial sorting variable. Table 8 shows that the alpha spread between extreme emission intensity quintiles is only significantly positive among stocks with higher institutional ownership which does not lend support to an explanation based on the information channel. Two other firm characteristics that have been used to proxy for informational frictions in the literature are firm size and analyst coverage. We have already seen that the pollution premium is stronger among larger firms. Furthermore, bivariate sorts of Table 7 indicate that the alpha spread between firms with high-

[21] We only report Q5PS alphas in this table to conserve space, however, FF6PS alphas produce qualitatively similar results.

and low-emission intensity is only significantly positive among firms with higher analyst following. These findings render an information-based story an unlikely culprit for the pollution premium.

Finally, we entertain the alternative explanation that, if stocks with high (low) emission intensity are relatively underpriced (overpriced), the arbitrage strategy that is long (short) in stocks with high (low) emission intensity boils down to industry pairs-trading that aims to profit from a certain mispricing within an industry. To test this conjecture, we conduct bivariate sorts using the mispricing measure (*MISP*) of Stambaugh et al. (2017) as the initial sorting variable. The final set of results in Table 8 do not provide evidence in favor of this hypothesis since the alpha spread between extreme scaled emission quintiles is significantly positive only among stocks that are less likely to be mispriced.

3.8 Earnings surprises

Although bivariate sorts of the prior section do not provide evidence for a mispricing-based story for the pollution premium, we now approach this question from a different avenue. A risk-based explanation for the pollution premium assumes that realized returns are a good proxy for expected returns, and thus, the cost of capital. However, a large literature on ESG investing uses realized abnormal returns as a measure of unexpected returns, and thus, mispricing rather than risk (Gompers et al., 2003; Fornell et al., 2006; Edmans, 2011; Lins et al., 2017). Practitioners also interpret the high alpha to certain ESG strategies as evidence that ESG is good for firm value and underpriced by the market, rather than bad for firm value and exposing companies to excessive risk. A standard way used by the literature to disentangle risk from mispricing is to study future earnings surprises (La Porta et al., 1997; Core et al., 2006).

If firms with higher emission intensities enjoy positive earnings surprises, one can think of at least two mispricing-based reasons. First, some companies may be focusing on long-term shareholder value and view toxic emissions as an externality that they do not have to pay for due to doubts about government intervention. Such firms do not spend resources to curb their emissions, deliver higher earnings and investors respond positively to these higher earnings since they also have doubts about government action. Second, some managers may suffer from short-termism and underinvest in emissions reduction compared to the level that would maximize long-term value. If investors are similarly myopic, they would respond positively to higher earnings.

Under both explanations, the market would not be fully pricing in risks related to environmental policy uncertainty.

We test this hypothesis by estimating pooled panel regressions of various earnings surprise metrics on contemporaneous or lagged emission intensity. We cluster all standard errors at the industry and year level, and all specifications include industry- and year-fixed effects. Panels A, B and C of Table 9 present results for specifications where the dependent variable is one-year earnings surprise (*SUE1*), two-year earnings surprise (*SUE2*) and long-term growth surprise (*LTG*), respectively. Findings indicate that neither contemporaneous nor lagged emission intensity has a statistically significant slope coefficient in the presence or absence of control variables in any panel. In other words, companies with higher emission intensities do not enjoy more positive earnings surprises which precludes the conjecture that the pollution premium is driven by mispricing tied to investors' responses to favorable earnings news.[22]

3.9 Divestment

Another possible explanation for the pollution premium is that socially responsible or ethical investors treat stocks of firms with high emission intensities as "sin stocks" (Fabozzi et al., 2008; Hong and Kacperczyk, 2009). Sustainable investment policies implemented by institutional investors may result in underdiversification due to divestment and exclusionary screening of stocks with higher scaled emissions. As a result, risk sharing would be limited, idiosyncratic risk would rise and, if the extent of such divestment is high, significant pricing effects could be observed. We test this conjecture by looking at the portfolio holdings of institutional investors and estimate a pooled regression model where the dependent variable is institutional ownership ratio, and the independent variable of interest is emission intensity. All standard errors are clustered at the industry and year level, and all specifications include year-month-fixed effects. Moreover, we try specifications where we include and exclude industry fixed-effects and/or the full set of control variables detailed earlier.

Results are presented in Table 10. In the first set of regressions, we use the aggregate institutional ownership ratio (*INST*) as the dependent variable. The slope coefficient of emission intensity is statistically insignificant in all specifications. Next, we disaggregate *INST* into its

[22] Hsu et al. (2023) find that firms with higher emission intensity have significantly higher contemporaneous profits, however, they use ROA and do not look at the unexpected component of earnings.

components motivated by the fact that the universe of institutional investors pools a number of different constituencies with possibly different investor pressures. For example, insurance companies and pension funds which have more long-term oriented investments may face higher investor pressure to divest from companies with high emission intensities compared to mutual funds that are incentivized to also generate short-term performance. Thus, we distribute all institutional investors into five categories, namely banks, insurance companies, investment companies (such as mutual funds), independent investment advisers and others (such as pension funds and hedge funds). For each category, we obtain firm-level institutional ownership ratios and estimate the pooled regression model for each of them separately. Table 10 shows that emission intensity has a significantly negative coefficient only when the dependent variable is institutional ownership by investment companies. In other words, there is some evidence that mutual funds are divesting from firms with high emission intensities which could account for some of the observed pollution premium. However, the economic effect of this divestment is small since, based on the univariate specification with industry fixed-effects, a one-standard-deviation increase in emission intensity leads to approximately 0.12% decline in ownership by investment companies.

4. Conclusion

Hsu et al. (2023) find that a long-short portfolio constructed from firms with high versus low toxic emission intensity within an industry generates significantly positive average abnormal returns. To explain this pollution premium, they propose a novel systematic risk related to environmental policy uncertainty and show that regime change risk is instrumental in pricing the cross-section of emission intensity portfolios. In our study, we examine the impact of various methodological choices and also entertain some alternative hypotheses for the pollution premium that are not considered in Hsu et al. (2023).

First, pollution premium is strictly an intra-industry phenomenon in the sense that investors penalize companies that pollute relatively more than their industry peers. However, they do not necessarily demand a return premium for stocks of firms that pollute relatively more than companies in other sectors. Second, it is total emissions scaled by proxies of firm size, but not the level of or growth in annual emissions that is priced at the cross-section. Third, we do not find consistent evidence that pollution premium got stronger during recent years as environmental concerns and potentially regime change risk became more pronounced. Fourth, we use an alternative set of control variables that are more standard in asset pricing studies and find that the positive relation between emission intensity and future returns is dependent on the existence of industry-fixed effects in a multivariate setting.

In terms of alternative explanations for the pollution premium, we first consider the impact of costly arbitrage and informational frictions. Our findings do not support these channels since the pollution premium is stronger among equities that are less subject to limits-to-arbitrage and informational uncertainties. Second, we investigate whether companies with high emission intensities enjoy higher earnings surprises to test a mispricing-based explanation, however, we do not find any supporting evidence. Third, we test whether higher returns to higher emission intensity-stocks are due to exclusionary screening and divestment activities of institutional investors. Although investment companies such as mutual funds have lower ownership in firms with higher scaled emissions, the economic magnitude of this effect is limited.

References

Akey, P., and I. Appel, 2021. The limits of limited liability: evidence from industrial pollution. *Journal of Finance* 76 (1), 5-55.

Albuquerque, R., Y. Koskinen, and C. Zhang, 2019. Corporate social responsibility and firm risk: theory and empirical evidence. *Management Science* 65 (10), 4451-4469.

Alessi, L., S. Battiston, and V. Kvedaras. 2024. Over with carbon? Investors' reaction to the Paris Agreement and the US withdrawal. *Journal of Financial Stability* 71, 101232.

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

Ang, A., R.J. Hodrick, Y. Xing, and X. Zhang, 2006. The cross-section of volatility and expected returns. *Journal of Finance* 61 (1), 259-299.

Ardia, D., K. Bluteau, K. Boudt, and K. Inghelbrecht, 2023. Climate change concerns and the performance of green vs. brown stocks. *Management Science* 69 (12), 7607-7632.

Aswani, J., A. Raghunandan, and S. Rajgopal, 2024a. Are carbon emissions associated with stock returns? *Review of Finance* 28 (1), 75-106.

Aswani, J., A. Raghunandan, and S. Rajgopal, 2024b. Are carbon emissions associated with stock returns? Reply. *Review of Finance* 28 (1), 111–115.

Atilgan, Y., A. Edmans, K.O. Demirtas, and A.D. Gunaydin, 2024. Does the carbon premium reflect risk or mispricing? Working paper.

Bali, T.G., S.J. Brown, and Y. Tang, 2017. Is economic uncertainty priced in the cross-section of stock returns? *Journal of Financial Economics* 126 (3), 471-489.

Bali, T.G., N. Cakici, and R.F. Whitelaw, 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. *Journal of Financial Economics* 99 (2), 427-446.

Barnett, M., 2023. Climate change and uncertainty: an asset pricing perspective. *Management Science* 69 (12), 7562-7584.

Bauer, R., T. Ruof, and P. Smeets, 2021. Get real! Individuals prefer more sustainable investments. *Review of Financial Analysis* 34 (8), 3976-4043.

Bloom, N., 2009. The impact of uncertainty shocks. *Econometrica* 77 (3), 623-685.

Bolton, P., and M. Kacperczyk, 2021. Do investors care about carbon risk? *Journal of Financial Economics* 142 (2), 517-549.

Bolton, P., and M. Kacperczyk, 2023. Global pricing of carbon-transition risk. *Journal of Finance* 78 (6), 3677–3754.

Bolton, P., and M. Kacperczyk, 2024. Are carbon emissions associated with stock returns? Comment. *Review of Finance* 28 (1), 107–109.

Brogaard, J., and A. Detzel, 2015. The asset-pricing implications of government economic policy uncertainty. *Management Science* 61 (1), 3-18.

Carhart, M.M., 1997. On persistence in mutual fund performance. *Journal of Finance* 52 (1), 57-82.

Cao, J., S. Titman, X. Zhan, and W. Zhang, 2023. ESG preference, institutional trading, and stock return patterns. *Journal of Financial and Quantitative Analysis* 58 (5), 1843-1877.

Chava, S., 2014. Environmental externalities and cost of capital. *Management Science* 60 (9), 2223-2247.

Chen, Y., A. Kumar, and C. Zhang, 2020. Dynamic ESG preferences and asset prices. Working paper.
Cooper, M.J., H. Gulen, and M.J. Schill, 2008. Asset growth and the cross-section of stock returns. *Journal of Finance* 63 (4), 1609-1651.

Core, J.E., R.G. Wayne, and T.O. Rusticus, 2006. Does weak governance cause weak stock returns? An examination of firm operating performance and investors' expectations. *Journal of Finance* 61 (2), 655–687.

Currie, J., L. Davis, M. Greenstone, and R. Walker, 2015. Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings. *American Economic Review* 105 (2), 678-709.

de Angelis, T., P. Tankov, and O.D. Zerbib, 2023. Climate impact investing. *Management Science* 69 (12), 7669-7692.

Dyck, A., K.V. Lins, L. Roth, and H.F. Wagner, 2019. Do institutional investors drive corporate social responsibility? International evidence. *Journal of Financial Economics* 131 (3), 693-714.

Easterwood, J.C., and S.R. Nutt, 1999. Inefficiency in analysts' earnings forecasts: systematic misreaction or systematic optimism? *Journal of Finance* 54 (5), 153–193.

Edmans, A., 2011. Does the stock market fully value intangibles? Employee satisfaction and equity prices. *Journal of Financial Economics* 101 (3), 621–640.

Fabozzi, F.J., K.C. Ma, and B.J. Oliphant, 2008. Sin stock returns. *Journal of Portfolio Management* 35 (1), 82-94.

Fama, E.F., and K.R. French, 1992. The cross-section of expected stock returns. *Journal of Finance* 47 (2), 427-465.

Fama, E.F., and K.R. French, 1993. Common risk factors in the returns of stocks and bonds. *Journal of Financial Economics* 33 (1), 3-56.

Fama, E.F., and K.R. French, 1997. Industry costs of equity. *Journal of Financial Economics* 43 (2), 153-193.

Fama, E.F., and K.R. French, 2015. A five-factor asset pricing model. *Journal of Financial Economics* 116 (1), 1-22.

Fama, E.F., and J. MacBeth, 1973. Risk, return and equilibrium: empirical tests. *Journal of Political Economy* 81 (3), 607-636.

Fornell, C., S. Mithas, F.V. Morgeson III, and M.S. Krishnan, 2006. Customer satisfaction and stock prices: high returns, low risk. *Journal of Marketing* 70 (1), 3–14.

Giroud, X., and H.M. Mueller, 2011. Corporate governance, product market competition, and equity prices. *Journal of Finance* 66 (2), 563–600.

Gompers, P., J. Ishii, and A. Metrick, 2003. Corporate governance and equity prices. *Quarterly Journal of Economics* 118 (1), 107–156.

Gu, L., D. Hackbarth, and T. Johnson, 2018. Inflexibility and stock returns. *Review of Financial Studies* 31 (1), 278-321.

Harvey, C.R., and A. Siddique, 2000. Conditional skewness in asset pricing tests. *Journal of Finance* 55 (3), 1263-1295.

Hatzmark, S.M., and A.B. Sussman, 2019. Do investors value sustainability? A natural experiment examining ranking and fund flows. *Journal of Finance* 74 (6), 2789-2837.

Heath, D., D. Macciocchi, R. Michaely, and M.C. Ringgenberg, 2023. Does socially responsible investing change corporate behavior? *Review of Finance* 27 (6), 2057-2083.

Heeb, F., J.F. Kölbel, F. Paetzold, and S. Zeisberger, 2023. Do investors care about impact? *Review of Financial Studies* 36 (5), 1737-1787.

Heinkel, R., A. Kraus, and J. Zechner, 2001. The effect of green investment on corporate behavior. *Journal of Financial and Quantitative Analysis* 36 (4), 431-449.

Hirshleifer, D., P.-H. Hsu, and D. Li, 2013. Innovative efficiency and stock returns. *Journal of Financial Economics* 107 (3), 632-654.

Hoepner, A.G.F., I. Oikonomou, Z. Sautner, L.T. Starks, and X.Y. Zhou, 2024. ESG shareholder engagement and downside risk. *Review of Finance* 28 (2), 438-510.

Hong, H., F.W. Li, and J. Xu, 2019. Climate risks and efficiency. *Journal of Econometrics* 208 (1), 265-281.

Hong, H., and M. Kacperczyk, 2009. The price of sin: the effects of social norms on capital markets. *Journal of Financial Economics* 93 (1), 15-36.

Hong, H., N. Wang, and J. Yang, 2023. Welfare consequences of sustainable finance. *Review of Financial Studies* 36 (12), 4864-4918.

Hou, K., H. Mo, C. Xue, and L. Zhang, 2021. An augmented *q*-factor model with expected growth. *Review of Finance* 25 (1), 1-41.

Hsu, P.-H., K. Li, and C.-Y. Tsou, 2023. The pollution premium. *Journal of Finance* 78 (3), 1343-1392.

Hwang, C.Y., S. Titman, and Y. Wang, 2022. Investor tastes, corporate behavior and stock returns: an analysis of corporate social responsibility. *Management Science* 68 (10), 7131-7152.

Ilhan, E., Z. Sautner, and G. Vilkov, 2021. Carbon tail risk. *Review of Financial Studies* 34 (3), 1540-1571.

Ilhan, E., P. Krueger, Z. Sautner, and L.T. Starks, 2023. Climate risk disclosure and institutional investors. *Review of Financial Studies* 36 (7), 2617-2650.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *Journal of Finance* 45 (3), 881-898.

Jegadeesh, N., and S. Titman, 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance* 48 (1), 65-91.

Jing, C., K. Keasey, I. Lim., and B. Xu, 2024. Analyst coverage and corporate environmental policies. *Journal of Financial and Quantitative Analysis* 59 (4), 1586-1619.

Kim, I., H. Wan, B. Wang, and T. Yang, 2019. Institutional investors and corporate environmental, social and governance policies: evidence from toxic release data. *Management Science* 65 (10), 4901-4926.

Krueger, P., 2015. Corporate goodness and shareholder wealth. *Journal of Financial Economics* 115 (2), 304-329.

Krueger, P., Z. Sautner, and L.T. Starks, 2020. The importance of climate risks. *Review of Financial Studies* 33 (3), 1067-1111.

La Porta, R., J. Lakonishok, A. Shleifer, and R. Vishny, 1997. Good news for value stocks: further evidence on market efficiency. *Journal of Finance* 52 (2), 859–874.

Li, D., 2011. Financial constraints, R&D investment, and stock returns. *Review of Financial Studies* 24 (9), 2974-3007.

Liang, H., L. Sun, and M. Teo, 2022. Responsible hedge funds. *Review of Finance* 26 (6), 1585-1633.

Lin, X., B. Palazzo, and F. Yang, 2020. The risks of old capital age: asset pricing implications of technology adoption. *Journal of Monetary Economics* 115, 145-161.

Lins, K.V., H. Servaes, and A. Tamayo, 2017. Social capital, trust, and firm performance: the value of corporate social responsibility during the financial crisis. *Journal of Finance* 72 (4), 1785–1824.

Monasterolo, I., and L. de Angelis, 2020. Blind to carbon risk? An analysis of stock market reaction to the Paris Agreement. *Ecological Economics* 170, 106571.

Newey, W.K., and K.D. West, 1987. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica* 55 (3), 703-708.

Novy-Marx, R., 2013. The other side of value: the gross profitability premium. *Journal of Financial Economics* 108 (1), 1-23.

Pastor, L., and R.F. Stambaugh, 2003. Liquidity risk and expected stock returns. *Journal of Political Economy* 111 (3), 642-685.

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

Pastor, L., R.F. Stambaugh, and L.A. Taylor, 2022. Dissecting green returns. *Journal of Financial Economics* 146 (2), 403-424.

Renneboog, L., J.T. Horst, and C. Zhang, 2008. The price of ethics and stakeholder governance: the performance of socially responsible mutual funds. *Journal of Corporate Finance* 14 (3), 302-322.

Riedl, A., and P. Smeets, 2017. Why do investors hold socially responsible mutual funds? *Journal of Finance* 72 (6), 2505-2550.

Shleifer, A., and R.W. Vishny, 1997. The limits of arbitrage. *Journal of Finance* 52 (1), 36-55.

Stambaugh, R.F., and Y. Yuan, 2017. Mispricing factors. *Review of Financial Studies* 30 (4), 1270-1315.

Stambaugh, R.F., J. Yu, and Y. Yuan, 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. *Journal of Finance* 70 (5), 1903-1948.

Xu, Q., and T. Kim, T., 2022. Financial constraints and corporate environmental policies. *Review of Financial Studies* 35 (2), 576-635.

Table 1
Univariate portfolio sorts

This table shows average one-month-ahead excess and abnormal returns for quintiles sorted on toxic emission intensity relative to industry peers. Emission intensity is defined as raw emissions scaled by total assets in Panel A, by property, plant, and equipment in Panel B, by sales in Panel C, and by market equity in Panel D. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. We also form an arbitrage portfolio that is long in high-emission intensity stocks and short in low-emission intensity stocks. The sample runs from October 1992 to September 2022 and excludes financial industries. Portfolio returns are either value-weighted by firms' market capitalization or equal-weighted and are multiplied by 12 to make their magnitudes comparable to annualized returns. We report two different alphas. FF6PS is the intercept term from a time-series regression of portfolio returns on the market, size, value, profitability and investment factors of Fama and French (2015) augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS is the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

	Value-Weighted						Equal-Weighted					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
	Panel A: Assets											
Return	5.77	8.91	8.55	8.33	11.91	6.13	12.45	10.69	11.64	14.09	16.65	4.19
	(1.76)	(2.73)	(2.66)	(2.59)	(3.17)	(2.64)	(3.58)	(2.95)	(2.90)	(3.95)	(4.34)	(3.79)
FF6PS	-2.83	1.48	-1.36	-2.28	0.64	3.47	0.62	-0.36	-0.03	2.29	4.41	3.79
	(-1.74)	(0.96)	(-0.94)	(-1.33)	(0.46)	(2.04)	(0.56)	(-0.25)	(-0.02)	(1.90)	(3.12)	(3.49)
Q5PS	-2.84	0.85	-2.92	-3.70	3.07	5.91	0.37	-0.73	0.12	1.55	4.68	4.31
	(-1.78)	(0.51)	(-2.15)	(-2.08)	(1.34)	(2.55)	(0.22)	(-0.42)	(0.06)	(0.91)	(2.54)	(3.85)
	Panel B: Plant, Property, Equipment											
Return	5.16	9.34	10.68	9.44	9.96	4.80	11.97	11.73	11.98	14.00	15.87	3.91
	(1.55)	(2.91)	(3.48)	(2.26)	(3.43)	(3.25)	(3.49)	(3.11)	(3.06)	(3.75)	(4.36)	(3.63)
FF6PS	-3.03	1.45	1.11	-2.83	0.00	3.03	0.18	0.28	0.31	2.58	3.61	3.44
	(-1.77)	(0.89)	(0.70)	(-1.62)	(0.00)	(1.74)	(0.17)	(0.21)	(0.20)	(1.83)	(2.87)	(3.03)
Q5PS	-2.95	0.61	-1.06	-2.41	0.70	3.65	0.17	0.35	-0.25	2.04	3.71	3.54
	(-1.74)	(0.39)	(-0.73)	(-0.83)	(0.66)	(1.95)	(0.10)	(0.22)	(-0.13)	(1.14)	(2.17)	(3.02)
	Panel C: Sales											
Return	5.10	9.79	9.13	8.44	11.10	6.00	12.40	10.99	12.35	13.57	16.22	3.82
	(1.56)	(2.86)	(2.72)	(2.62)	(3.00)	(2.59)	(3.55)	(3.04)	(3.17)	(3.74)	(4.15)	(3.24)
FF6PS	-3.40	2.76	-1.30	-2.16	0.45	3.85	0.55	0.08	0.67	1.37	4.28	3.73
	(-2.04)	(1.45)	(-0.90)	(-1.15)	(0.32)	(2.08)	(0.54)	(0.05)	(0.50)	(1.11)	(2.94)	(3.33)
Q5PS	-3.18	2.10	-2.85	-3.13	2.20	5.37	0.53	-0.22	0.12	0.96	4.62	4.08
	(-1.98)	(1.14)	(-2.20)	(-1.71)	(1.00)	(2.19)	(0.33)	(-0.13)	(0.06)	(0.53)	(2.53)	(3.60)
	Panel D: Market Value of Equity											
Return	5.04	10.65	8.51	12.76	9.65	4.61	11.31	11.03	11.84	13.95	17.65	6.34
	(1.48)	(3.64)	(2.67)	(3.08)	(3.27)	(2.57)	(3.48)	(3.16)	(3.16)	(3.63)	(4.09)	(3.81)
FF6PS	-2.31	1.35	-1.93	-0.50	-0.13	2.18	0.23	-0.49	0.21	2.47	4.59	4.36
	(-1.29)	(1.02)	(-1.25)	(-0.33)	(-0.09)	(1.22)	(0.24)	(-0.35)	(0.16)	(1.75)	(2.82)	(3.03)
Q5PS	-2.70	0.06	-3.73	0.86	0.87	3.57	-0.15	-1.24	0.35	1.60	5.64	5.79
	(-1.60)	(0.04)	(-1.99)	(0.30)	(0.74)	(2.20)	(-0.11)	(-0.68)	(0.20)	(0.88)	(2.65)	(3.85)

Table 2
Univariate portfolio sorts across industries

This table shows average one-month-ahead excess and abnormal returns for quintiles sorted on toxic emission intensity relative to all sample firms. Emission intensity is defined as raw emissions scaled by total assets in Panel A, by property, plant, and equipment in Panel B, by sales in Panel C, and by market equity in Panel D. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We rebalance portfolios at the end of each September. We also form an arbitrage portfolio that is long in high-emission intensity stocks and short in low-emission intensity stocks. The sample runs from October 1992 to September 2022 and excludes financial industries. Portfolio returns are either value-weighted by firms' market capitalization or equal-weighted and are multiplied by 12 to make their magnitudes comparable to annualized returns. We report two different alphas. FF6PS is the intercept term from a time-series regression of portfolio returns on the market, size, value, profitability and investment factors of Fama and French (2015) augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS is the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

	Value-Weighted						Equal-Weighted					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
						Panel A: Assets						
Return	6.39	7.93	9.21	10.95	9.42	3.03	12.47	12.16	11.89	13.43	15.34	2.87
	(1.92)	(2.36)	(2.65)	(2.82)	(3.10)	(1.70)	(3.62)	(3.42)	(3.06)	(3.86)	(3.50)	(1.44)
FF6PS	-2.21	0.65	-0.33	-0.94	-1.50	0.71	1.13	1.09	0.84	1.70	1.95	0.81
	(-1.38)	(0.38)	(-0.23)	(-0.55)	(-1.13)	(0.41)	(0.93)	(0.87)	(0.52)	(1.35)	(1.10)	(0.45)
Q5PS	-2.18	-1.01	-1.97	-0.08	0.08	2.26	0.56	0.76	-0.76	2.07	3.12	2.55
	(-1.33)	(-0.60)	(-1.19)	(-0.03)	(0.05)	(1.06)	(0.36)	(0.45)	(-0.36)	(1.24)	(1.30)	(1.33)
						Panel B: Plant, property, equipment						
Return	6.16	8.59	10.76	8.53	10.09	3.93	12.73	10.81	12.66	14.04	15.07	2.34
	(1.97)	(2.39)	(3.03)	(2.49)	(3.14)	(2.14)	(3.87)	(3.09)	(3.38)	(3.52)	(3.66)	(1.37)
FF6PS	-1.79	1.07	0.81	-3.30	-1.71	0.08	1.22	0.57	1.31	1.88	1.76	0.54
	(-1.07)	(0.72)	(0.66)	(-1.81)	(-1.23)	(0.04)	(1.12)	(0.40)	(1.03)	(1.31)	(1.17)	(0.36)
Q5PS	-1.73	-0.90	0.32	-2.90	-0.28	1.45	0.88	-0.39	0.41	2.79	2.10	1.22
	(-1.07)	(-0.58)	(0.18)	(-1.29)	(-0.20)	(0.68)	(0.56)	(-0.21)	(0.23)	(1.56)	(1.03)	(0.77)
						Panel C: Sales						
Return	5.62	9.66	10.13	12.18	8.01	2.39	13.04	12.13	12.31	13.20	14.59	1.56
	(1.79)	(2.85)	(2.93)	(2.92)	(2.99)	(1.39)	(3.64)	(3.30)	(3.12)	(3.84)	(3.55)	(0.80)
FF6PS	-3.35	0.78	0.65	-0.24	-1.38	1.97	1.46	1.07	0.63	1.47	2.08	0.63
	(-2.00)	(0.55)	(0.39)	(-0.13)	(-1.16)	(1.16)	(1.15)	(0.73)	(0.44)	(1.13)	(1.27)	(0.35)
Q5PS	-4.25	1.43	-2.47	0.81	-0.49	3.76	1.11	1.07	-1.26	1.70	3.11	2.01
	(-2.36)	(0.89)	(-1.48)	(0.27)	(-0.45)	(1.94)	(0.66)	(0.61)	(-0.64)	(1.05)	(1.34)	(1.05)
						Panel D: Market value of equity						
Return	5.55	10.29	12.28	9.04	11.69	6.14	11.40	12.35	12.29	13.03	16.25	4.85
	(1.70)	(2.94)	(2.95)	(3.29)	(3.95)	(2.21)	(3.63)	(3.50)	(3.06)	(3.76)	(3.49)	(2.10)
FF6PS	-1.63	1.17	-1.60	-0.94	0.22	1.85	1.08	1.17	0.39	0.89	3.16	2.09
	(-0.98)	(0.81)	(-0.74)	(-0.73)	(0.13)	(0.93)	(1.03)	(0.93)	(0.24)	(0.72)	(1.66)	(1.11)
Q5PS	-2.00	-0.93	-1.63	-0.40	0.65	2.65	0.74	0.22	-0.95	0.74	5.01	4.27
	(-1.22)	(-0.64)	(-0.50)	(-0.32)	(0.33)	(1.16)	(0.52)	(0.14)	(-0.49)	(0.43)	(1.91)	(2.05)

Table 3
Level of and growth in emissions

This table shows average one-month-ahead excess and abnormal returns for quintiles sorted on the level of raw emissions in Panel A and annual percentage growth in raw emissions in Panel B relative to industry peers. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. We also form an arbitrage portfolio that is long in stocks with high emission levels or growths and short in stocks with low emission levels or growths. The sample runs from October 1992 to September 2022 and excludes financial industries. Portfolio returns are either value-weighted by firms' market capitalization or equal-weighted and are multiplied by 12 to make their magnitudes comparable to annualized returns. We report two different alphas. FF6PS is the intercept term from a time-series regression of portfolio returns on the market, size, value, profitability and investment factors of Fama and French (2015) augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS is the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

	Value-Weighted						Equal-Weighted					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
Panel A: Level of emissions												
Return	6.80	4.94	9.47	8.86	9.87	3.06	12.95	12.73	13.41	13.07	13.13	0.19
	(2.62)	(1.70)	(2.78)	(2.91)	(2.67)	(1.15)	(3.49)	(3.34)	(3.60)	(3.59)	(3.52)	(0.14)
FF6PS	-1.91	-4.12	0.79	-0.28	-0.38	1.52	1.76	1.16	2.14	0.95	0.60	-1.16
	(-1.11)	(-2.24)	(0.33)	(-0.19)	(-0.29)	(0.79)	(1.49)	(0.79)	(1.62)	(0.59)	(0.49)	(-0.90)
Q5PS	-1.35	-5.08	-0.08	-0.25	-0.85	0.50	2.37	0.99	1.20	0.20	0.83	-1.54
	(-0.78)	(-2.47)	(-0.04)	(-0.18)	(-0.47)	(0.20)	(1.44)	(0.55)	(0.66)	(0.10)	(0.48)	(-1.12)
Panel B: Growth in emissions												
Return	5.45	7.85	7.16	9.47	11.47	6.02	10.83	12.33	13.50	14.02	12.20	1.37
	(1.66)	(2.09)	(2.18)	(2.64)	(3.01)	(1.72)	(2.82)	(3.39)	(3.42)	(3.98)	(3.04)	(1.05)
FF6PS	-3.19	-1.56	-1.62	0.89	-0.40	2.79	-0.15	0.05	1.34	2.74	0.60	0.75
	(-1.82)	(-0.81)	(-0.94)	(0.53)	(-0.20)	(0.99)	(-0.10)	(0.04)	(1.01)	(2.24)	(0.40)	(0.48)
Q5PS	-2.96	-2.82	-1.70	-0.25	1.16	4.12	0.20	-0.03	1.30	1.98	0.98	0.78
	(-1.54)	(-1.46)	(-0.97)	(-0.17)	(0.41)	(1.15)	(0.11)	(-0.02)	(0.71)	(1.20)	(0.51)	(0.48)

Table 4
Subperiod analysis

This table shows average one-month-ahead value-weighted excess and abnormal returns for quintiles sorted on toxic emission intensity relative to industry peers. Emission intensity is defined as raw emissions scaled by total assets in Panel A, by property, plant, and equipment in Panel B, by sales in Panel C, and by market equity in Panel D. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. We also form an arbitrage portfolio that is long in high-emission intensity stocks and short in low-emission intensity stocks. The sample runs from October 1992 to September 2022 and excludes financial industries. We report separate results for the subsample between 1992 and 2006, and the subsample between 2007 and 2022. Portfolio returns are multiplied by 12 to make their magnitudes comparable to annualized returns. We report two different alphas. FF6PS is the intercept term from a time-series regression of portfolio returns on the market, size, value, profitability and investment factors of Fama and French (2015) augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS is the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). t-statistics are based on standard errors using the Newey-West correction for 12 lags.

	1992-2006						2007-2022					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
						Panel A: Assets						
Return	5.82	8.35	7.07	6.82	9.56	3.75	5.73	9.41	9.89	9.71	14.04	8.31
	(1.46)	(1.61)	(1.67)	(1.61)	(2.58)	(2.27)	(1.13)	(2.32)	(2.08)	(2.04)	(2.23)	(2.03)
FF6PS	-1.58	5.30	-2.59	-2.97	0.72	2.30	-2.67	0.32	0.42	0.27	2.54	5.21
	(-1.02)	(2.24)	(-1.14)	(-1.18)	(0.49)	(1.35)	(-1.06)	(0.19)	(0.24)	(0.16)	(1.04)	(1.80)
Q5PS	-2.60	-0.53	-5.50	-6.80	0.87	3.47	-2.53	0.40	-0.61	-0.21	6.35	8.88
	(-1.43)	(-0.17)	(-3.01)	(-2.46)	(0.51)	(2.02)	(-1.12)	(0.23)	(-0.36)	(-0.13)	(1.81)	(2.29)
						Panel B: Plant, property, equipment						
Return	4.58	10.50	11.09	4.82	9.95	5.37	5.69	8.28	10.32	13.64	9.96	4.27
	(1.10)	(2.21)	(2.83)	(1.11)	(2.57)	(3.11)	(1.12)	(1.91)	(2.22)	(2.02)	(2.32)	(1.82)
FF6PS	-1.78	6.69	-0.03	-4.61	1.88	3.66	-2.66	-1.00	2.09	1.41	-0.03	2.63
	(-0.90)	(2.44)	(-0.01)	(-2.10)	(1.11)	(1.56)	(-1.04)	(-0.67)	(0.92)	(0.56)	(-0.02)	(1.04)
Q5PS	-3.16	1.75	-4.22	-8.22	1.87	5.04	-2.59	-0.99	0.67	4.11	0.77	3.37
	(-1.64)	(0.61)	(-1.74)	(-3.48)	(0.87)	(1.89)	(-1.09)	(-0.72)	(0.30)	(1.19)	(0.59)	(1.28)
						Panel C: Sales						
Return	4.95	9.59	10.28	5.57	9.08	4.13	5.23	9.97	8.09	11.05	12.94	7.71
	(1.27)	(1.70)	(2.16)	(1.43)	(2.35)	(2.61)	(1.01)	(2.46)	(1.71)	(2.24)	(2.12)	(1.87)
FF6PS	-2.27	7.67	-0.75	-3.88	0.51	2.78	-3.03	0.98	-1.49	1.55	1.85	4.88
	(-1.44)	(2.63)	(-0.32)	(-1.50)	(0.33)	(1.47)	(-1.16)	(0.59)	(-0.85)	(0.80)	(0.70)	(1.50)
Q5PS	-2.85	1.70	-4.14	-6.99	0.53	3.38	-3.02	1.06	-2.15	1.24	4.96	7.98
	(-1.53)	(0.52)	(-1.84)	(-2.60)	(0.31)	(1.91)	(-1.27)	(0.61)	(-1.25)	(0.73)	(1.42)	(1.96)
						Panel D: Market value of equity						
Return	5.27	11.94	6.24	9.24	11.33	6.06	4.83	9.47	10.58	15.96	8.12	3.29
	(1.17)	(2.81)	(1.62)	(2.46)	(3.05)	(2.18)	(0.95)	(2.36)	(2.15)	(2.27)	(1.81)	(1.45)
FF6PS	1.29	2.16	-4.18	-0.94	1.00	-0.29	-3.63	1.21	0.98	3.17	-0.90	2.73
	(0.59)	(1.18)	(-1.88)	(-0.45)	(0.55)	(-0.12)	(-1.49)	(0.75)	(0.67)	(1.36)	(-0.50)	(1.24)
Q5PS	-2.03	-1.42	-8.23	-4.27	2.08	4.11	-3.80	0.74	0.49	6.81	-0.29	3.51
	(-1.05)	(-0.63)	(-3.20)	(-1.80)	(1.23)	(1.87)	(-1.64)	(0.43)	(0.30)	(1.72)	(-0.19)	(1.60)

Table 5
Portfolio characteristics

This table reports the time-series average of the cross-sectional means of various control variables for quintiles sorted on toxic emission intensity relative to industry peers. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. We also form an arbitrage portfolio that is long in high-emission intensity stocks and short in low-emission intensity stocks. The sample runs from October 1992 to September 2022 and excludes financial industries. *Beta* is the market beta of each stock with respect to the value-weighted market index calculated from daily returns during the past year. *STR* is the return of a stock in the previous month. *Size* is the logarithm of market value of equity. *BM* is the ratio of the book value of equity to the market value of equity. *MOM* is the cumulative return of a stock during the past 11 months after skipping one month. *Illiq* is Amihud's illiquidity ratio calculated as the absolute daily return of a stock divided by its daily dollar trading volume (in millions) averaged over the month. *Coskew* is the co-skewness calculated as the coefficient of the squared excess market return term from a regression of the daily excess returns of a stock on the daily excess market returns and the squared daily excess market returns in the past year. *IVOL* is the standard deviation of error terms calculated from the application of the three-factor model of Fama and French (1993) to daily stock returns within a month. *MAX* is the average of the five highest daily returns of each stock in each month. *OP* is the ratio of earnings before interest and taxes to shareholders' equity. *IA* is the annual growth rate of total assets.

	L	2	3	4	H	H-L	t-stat
Emission Int.	39.61	253.69	923.28	2,835.18	23,151.24	23,111.62	(6.08)
Beta	1.00	0.99	1.05	1.01	1.01	0.01	(0.99)
STR	1.16	1.08	1.14	1.31	1.56	0.40	(4.76)
Size	14.32	14.08	14.28	14.24	13.86	-0.47	(-11.56)
BM	0.76	0.78	0.71	0.75	0.68	-0.08	(-2.67)
MOM	13.16	12.11	13.41	15.97	19.07	5.91	(5.29)
Illiq	0.70	1.09	1.95	1.31	1.50	0.80	(1.94)
Coskew	-1.92	-1.49	-0.93	-1.83	-1.49	0.43	(1.27)
IVOL	1.99	2.05	2.08	2.00	2.11	0.12	(5.04)
MAX	2.99	3.06	3.13	3.02	3.17	0.19	(5.89)
OP	0.00	0.02	0.14	0.02	0.02	0.02	(0.99)
IA	0.10	0.11	0.10	0.10	0.10	-0.01	(-0.79)

Table 6
Bivariate portfolio sorts
This table shows average one-month-ahead value-weighted abnormal returns for bivariate portfolios sorted on toxic emission intensity and various control variables. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. The sample runs from October 1992 to September 2022 and excludes financial industries. Each month, within each industry, stocks are sorted into two groups based on the median value for various control variables that are defined in Table 5. Next, each group of stocks is sorted into quintiles based on emission intensity to generate 2×5 portfolios within each industry. Subsequently, we aggregate each of the emission intensity-sorted portfolios across industries and the two control variable groups producing portfolios with dispersion in emission intensity that are similar in terms of the control variables. In addition, we form an arbitrage portfolio that is long in the resulting high-emission intensity portfolio and short in the resulting low-emission intensity portfolio. We report two different alphas which are multiplied by 12 to make their magnitudes comparable to annualized alphas. FF6PS is the intercept term from a time-series regression of portfolio returns on the market, size, value, profitability and investment factors of Fama and French (2015) augmented by the momentum factor of Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Q5PS is the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

	FF6PS						Q5PS					
	L	2	3	4	H	H-L	L	2	3	4	H	H-L
Beta	-1.63	-0.59	-0.69	-1.11	-0.07	1.56	-2.07	-1.24	-1.74	-2.40	1.76	3.83
	(-1.03)	(-0.37)	(-0.54)	(-0.64)	(-0.05)	(0.84)	(-1.31)	(-0.79)	(-1.28)	(-1.40)	(1.01)	(1.97)
STR	-1.30	0.18	1.68	-3.06	-0.70	0.60	-2.13	0.04	-0.22	-3.45	0.49	2.62
	(-0.81)	(0.12)	(1.16)	(-1.67)	(-0.49)	(0.35)	(-1.45)	(0.03)	(-0.20)	(-1.58)	(0.35)	(1.60)
Size	-0.97	0.24	-0.67	-1.21	0.17	1.13	-0.92	0.63	-2.00	-2.49	-0.06	0.85
	(-0.79)	(0.17)	(-0.56)	(-1.01)	(0.11)	(0.71)	(-0.67)	(0.48)	(-1.51)	(-1.79)	(-0.04)	(0.49)
BM	-1.49	0.36	-1.00	-2.46	-1.11	0.38	-1.76	0.08	-2.67	-3.51	-1.02	0.74
	(-1.02)	(0.20)	(-0.60)	(-1.63)	(-0.87)	(0.26)	(-1.10)	(0.05)	(-1.46)	(-1.95)	(-0.61)	(0.42)
MOM	-2.06	3.01	-2.03	-0.26	-0.59	1.47	-2.43	3.03	-3.14	-1.63	0.06	2.49
	(-1.35)	(1.49)	(-1.55)	(-0.16)	(-0.41)	(0.90)	(-1.66)	(1.80)	(-2.35)	(-0.86)	(0.04)	(1.49)
Illiq	-1.22	0.20	-1.69	-1.16	0.52	1.75	-1.34	0.38	-3.15	-2.24	0.93	2.27
	(-0.98)	(0.14)	(-1.36)	(-0.78)	(0.38)	(1.12)	(-0.94)	(0.29)	(-1.90)	(-1.39)	(0.55)	(1.30)
Coskew	-2.94	1.55	-0.78	-2.75	0.81	3.74	-3.53	2.02	-1.70	-3.14	1.83	5.35
	(-1.70)	(1.09)	(-0.55)	(-1.46)	(0.64)	(2.11)	(-1.87)	(1.72)	(-1.18)	(-1.36)	(1.42)	(2.96)
IVOL	-3.15	1.87	-1.36	-1.03	-0.03	3.12	-2.99	1.35	-2.34	-0.79	0.55	3.54
	(-2.16)	(0.95)	(-0.86)	(-0.53)	(-0.02)	(1.82)	(-2.13)	(0.72)	(-1.58)	(-0.31)	(0.38)	(1.83)
MAX	-3.16	0.95	0.21	-1.74	-0.60	2.56	-2.56	0.41	-0.94	-2.49	0.25	2.81
	(-2.03)	(0.59)	(0.13)	(-0.78)	(-0.47)	(1.33)	(-1.75)	(0.23)	(-0.59)	(-0.89)	(0.19)	(1.49)
OP	-2.70	-0.38	-1.62	-4.92	0.50	3.21	-2.93	-1.61	-3.53	-4.69	1.15	4.08
	(-1.83)	(-0.29)	(-1.18)	(-2.95)	(0.42)	(1.79)	(-2.06)	(-1.32)	(-2.48)	(-1.77)	(0.87)	(2.23)
IA	-1.85	1.35	-0.51	-2.12	0.51	2.36	-2.22	0.31	-1.57	-3.07	1.15	3.36
	(-1.17)	(0.82)	(-0.39)	(-1.13)	(0.43)	(1.44)	(-1.32)	(0.22)	(-1.24)	(-1.48)	(0.69)	(1.61)

Table 7
Fama-Macbeth regressions
This table reports Fama-MacBeth regressions of individual stock excess returns on emission intensity in natural logarithm and other firm characteristics. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We conduct cross-sectional regressions for each month from October of year *t* to September of year *t*+1. In each month, monthly returns of individual stock returns (annualized by multiplying by 12) are regressed on emission intensity in natural logarithm of year *t*-1 (that is reported by the end of September of year *t*) and different sets of control variables known by the end of September of year *t*. Control variables are defined in Table 5. We estimate the specifications with or without industry fixed-effects based on Fama and French (1997) 49-industry classifications. *t*-statistics are based on standard errors estimated using the Newey-West correction with 12 lags. The sample period is from October 1992 to September 2022.

	With industry fixed-effects					Without industry fixed-effects				
	1	2	3	4	5	1	2	3	4	5
Emission	0.550	0.560	0.439	0.457	0.427	0.369	0.367	0.215	0.205	0.175
	(3.56)	(3.58)	(2.77)	(2.85)	(2.79)	(1.99)	(2.11)	(1.26)	(1.18)	(1.05)
Beta		-0.463	1.436	1.520	1.685		2.870	4.077	3.990	4.183
		(-0.21)	(0.56)	(0.61)	(0.67)		(0.92)	(1.28)	(1.28)	(1.35)
STR		-0.062	-0.042	-0.092	-0.104		-0.042	-0.015	-0.090	-0.109
		(-0.63)	(-0.43)	(-0.72)	(-0.86)		(-0.43)	(-0.16)	(-0.73)	(-0.94)
Size			-1.456	-1.120	-1.148			-1.725	-1.439	-1.449
			(-2.57)	(-2.28)	(-2.27)			(-2.57)	(-2.69)	(-2.66)
BM			1.372	1.113	0.774			1.376	1.093	0.806
			(1.34)	(1.25)	(0.84)			(1.50)	(1.32)	(0.92)
MOM			-0.040	-0.032	-0.033			-0.037	-0.030	-0.032
			(-2.00)	(-1.78)	(-1.93)			(-1.69)	(-1.49)	(-1.66)
Illiq				0.016	0.013				0.013	0.011
				(0.90)	(0.73)				(0.82)	(0.67)
Coskew				-0.081	-0.059				-0.080	-0.068
				(-0.81)	(-0.67)				(-0.90)	(-0.84)
IVOL				-2.029	-2.233				-2.244	-2.466
				(-1.37)	(-1.60)				(-1.49)	(-1.70)
MAX				1.449	1.701				1.707	2.011
				(1.41)	(1.72)				(1.64)	(1.99)
OP					-1.920					-2.189
					(-0.15)					(-0.17)
IA					-4.268					-2.987
					(-2.46)					(-1.64)
Adj R^2	0.047	0.072	0.100	0.120	0.127	0.002	0.047	0.082	0.103	0.111
Obs	111,753	111,735	103,218	103,216	102,664	111,753	111,735	103,218	103,216	102,664

Table 8
Costly arbitrage, information frictions and mispricing

This table shows average one-month-ahead value-weighted abnormal returns for bivariate portfolios sorted on toxic emission intensity and various firm characteristics that are associated with limits-to-arbitrage, informational frictions and mispricing. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. We use the Fama and French (1997) 49 industry classifications and rebalance portfolios at the end of each September. *Size* and *Illiq* are defined in Table 5. *AGE* is the number of months that a stock has been listed on the CRSP database. *INST* is institutional ownership ratio, calculated by dividing the institutional ownership level computed using equity holdings by institutions that file 13F reports divided by total shares outstanding at quarter end. *CVRG* is the number of analysts covering the stock in the I/B/E/S database. *MISP* is the mispricing measure created by ranking stocks independently based on 11 return anomalies in such an order that a higher rank is associated with lower one-month-ahead stock returns, as documented in Stambaugh, Yu, and Yuan (2017). The mispricing measure is defined as the arithmetic average of the ranks of the 11 anomalies with a minimum of five of them available. The sample runs from October 1992 to September 2022 and excludes financial industries. Each month, within each industry, stocks are sorted into two groups based on the median value for these firm characteristics. Next, each group of stocks is sorted into quintiles based on emission intensity to generate 2×5 portfolios within each industry. After aggregating across industries, for both firm characteristic groups, we form an arbitrage portfolio that is long in high-emission intensity stocks and short in low-emission intensity stocks. We report Q5PS alphas (which are multiplied by 12 to make their magnitudes comparable to annualized alphas) calculated as the intercept term from a time-series regression of portfolio returns on the market, size, profitability, investment and expected growth factors of Hou et al. (2021) augmented by the liquidity factor of Pastor and Stambaugh (2003). *t*-statistics are based on standard errors using the Newey-West correction for 12 lags.

		L	2	3	4	H	H-L
Size	Low	2.04	-2.28	-1.20	-0.60	-0.48	-2.52
		(0.96)	(-1.10)	(-0.47)	(-0.33)	(-0.21)	(-1.06)
	High	-3.00	1.20	-3.24	-3.84	3.36	6.36
		(-1.76)	(0.64)	(-2.16)	(-2.07)	(1.34)	(2.57)
Illiq	Low	-3.00	1.20	-3.00	-3.84	3.24	6.24
		(-1.79)	(0.64)	(-2.03)	(-2.11)	(1.30)	(2.55)
	High	0.96	-3.36	-3.60	0.36	0.72	-0.24
		(0.46)	(-1.50)	(-1.35)	(0.12)	(0.30)	(-0.09)
AGE	Low	-5.28	0.24	-0.12	-3.12	5.04	10.32
		(-2.20)	(0.09)	(-0.07)	(-1.11)	(1.20)	(2.13)
	High	-1.20	1.32	-3.00	-3.36	0.96	2.16
		(-0.57)	(0.62)	(-1.75)	(-1.88)	(0.75)	(1.16)
INST	Low	-2.04	11.28	-2.04	-3.84	3.00	5.04
		(-0.93)	(0.19)	(-0.96)	(-2.09)	(1.00)	(1.55)
	High	-3.48	0.12	-3.00	-2.40	0.60	4.08
		(-2.03)	(0.04)	(-1.44)	(-1.27)	(0.37)	(1.85)
CVRG	Low	-0.36	-0.24	-3.12	0.72	2.64	3.00
		(-0.12)	(-0.10)	(-1.22)	(0.31)	(1.09)	(0.94)
	High	-3.00	1.20	-3.24	-4.20	3.12	6.12
		(-1.79)	(0.61)	(-1.80)	(-2.27)	(1.16)	(2.25)
MISP	Low	-4.08	1.32	-4.56	-6.12	0.00	4.08
		(-2.52)	(0.56)	(-2.46)	(-2.73)	(-0.03)	(2.33)
	High	-0.36	-1.92	-2.40	-6.24	-2.16	-1.68
		(-0.18)	(-0.76)	(-0.91)	(-2.19)	(-0.81)	(-0.51)

Table 9
Earnings surprises

This table presents results from pooled panel regressions of earnings surprises on contemporaneous or lagged emission intensity. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. The sample runs from October 1992 to September 2022 and excludes financial industries. *SUE1* (*SUE2*) is the one-year (two-year) earnings surprise measured as the actual EPS minus the I/B/E/S median analyst forecast 8 (20) months prior to the end of the forecast period, scaled by stock price. *LTG* is the long-term growth surprise measured as the actual five-year annualized EPS growth rate minus the I/B/E/S median analyst long-term growth forecast from 56 months earlier. We only report slope coefficients for emission intensity and suppress those for the control variables. All standard errors are clustered at the industry and year level, and all regressions include industry- and year-fixed effects. The only independent variable in specifications 1 and 3 is emission intensity whereas specifications 2 and 4 control for firm size and book-to-market ratio as defined in Table 5.

	1	2	3	4
		Panel A: SUE1		
Emission Int.	0.002	0.004		
	(0.87)	(0.97)		
Lagged Emission Int.			0.003	0.004
			(0.45)	(0.71)
Controls	No	Yes	No	Yes
Adj R^2	0.050	0.059	0.047	0.054
Obs	9,089	8,399	8,906	8,226
		Panel B: SUE2		
Emission Int.	0.010	0.013		
	(1.11)	(1.49)		
Lagged Emission Int.			0.008	0.009
			(0.91)	(1.10)
Controls	No	Yes	No	Yes
Adj R^2	0.082	0.086	0.085	0.088
Obs	8,016	7,391	7,952	7,362
		Panel C: LTG		
Emission Int.	77.166	68.333		
	(0.78)	(0.73)		
Lagged Emission Int.			110.241	107.708
			(1.21)	(1.31)
Controls	No	Yes	No	Yes
Adj R^2	0.095	0.100	0.084	0.086
Obs	1,073	1,008	1,143	1,075

Table 10
Divestment

This table presents results from pooled panel regressions of institutional ownership on emission intensity and various control variables defined in Table 5. Emission intensity is defined as raw emissions scaled by total assets. Raw emissions are measured as the sum of all toxic emissions in pounds produced in all plants owned by a firm. The sample runs from October 1992 to September 2022 and excludes financial industries. INST is institutional ownership ratio, calculated as the ratio of the institutional ownership level computed using equity holdings by institutions that file 13F reports to total shares outstanding at quarter end. INST_BANK, INST_INSUR, INST_INVEST, INST_ADVISER and INST_OTHER are institutional ownership ratio by banks, insurance companies, investment companies (e.g. mutual funds), independent investment advisors and other institutions (such as pension funds, sovereign wealth funds, hedge funds), respectively. We only report slope coefficients for emission intensity and suppress those for the control variables. All standard errors are clustered at the industry and year level, and all regressions include year-month-fixed effects. The only independent variable in specifications 1 and 2 is emission intensity whereas specifications 3 and 4 feature the whole set of control variables. Specifications 1 and 3 do not include industry-fixed effects whereas specifications 2 and 4 do.

	1	2	3	4
INST	-0.116	-0.151	-0.012	-0.038
	(-0.93)	(-1.27)	(-0.13)	(-0.40)
INST_BANK	-0.029	-0.031	0.002	0.001
	(-1.05)	(-1.32)	(0.12)	(0.04)
INST_INSUR	-0.015	-0.018	-0.006	-0.010
	(-1.35)	(-1.85)	(-0.74)	(-1.26)
INST_INVEST	-0.023	-0.027	-0.013	-0.019
	(-2.57)	(-5.14)	(-1.96)	(-3.65)
INST_ADVISER	-0.005	-0.004	0.008	0.010
	(-0.13)	(-0.11)	(0.23)	(0.31)
INST_OTHER	-0.051	-0.076	-0.009	-0.028
	(-1.03)	(-1.41)	(-0.22)	(-0.65)
Controls	No	No	Yes	Yes
Industry FE	No	Yes	No	Yes