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Ravi Jagannathan
Iwan Meier
Valeri Sokolovski

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ABSTRACT

Between 2016 and 2023, the top 10% of carbon-emission-intensive firms (heavy emitters) accounted for over 90% of all Scope 1 emissions from U.S. public companies. We observe that about 35% of the market capitalization of 'Value' portfolios, compared to 5% of 'Growth' portfolios, regardless of how Value and Growth are defined, was comprised of heavy emitters. When we split the Big Value portfolio into heavy- and light-emitter stocks, we find that these two portfolios had similar realized (raw and risk-adjusted) returns and expected returns, as measured by Implied Cost of Capital, suggesting limited incremental compensation for transition risk. We also find that Big Growth low-emitter stocks consistently had lower expected returns than Big Value low-emitter stocks, with the spread widening in recent years, despite similar emission levels. This indicates that factors beyond climate concerns are necessary to fully explain the superior performance of Growth stocks relative to Value stocks over the past decade.

Ravi Jagannathan
Kellogg Graduate School of Management
Northwestern University
2211 Campus Drive
Evanston, IL 60208
and NBER
rjaganna@kellogg.northwestern.edu

Valeri Sokolovski
Alberta School of Business
University of Alberta
11211 Saskatchewan Drive NW
Edmonton, AB T6G 2R6
Canada
vsokolov@ualberta.ca

Iwan Meier
HEC Montreal
3000, chemin de la Cote-Sainte-Catherine
Montreal (Quebec) H3T 2A7
Canada
iwan.meier@hec.ca

1 Introduction

The battle against climate change is recognized as one of the most significant challenges facing society today. To tackle the climate crisis, the world needs to reduce its emissions. As we transition toward this low-emissions future through technological change or consumer, investor, and governmental action, heavy-emitting firms (i.e., 'brown' firms) could likely be adversely affected.[1] Consequently, investors holding these firms in their portfolios may face significant exposure to carbon transition risk. While theory suggests that investors should be compensated for this risk (Pástor, Stambaugh, and Taylor, 2021; Pedersen, Fitzgibbons, and Pomorski, 2021), there is no consensus in the empirical literature on whether they are compensated or what the appropriate level of compensation should be.[2] Hence, it is important for investors to first understand the share of brown firms in their portfolios and, second, whether the market is offering any additional premiums for investing in these firms.

Factor investing has become a popular investment approach, possibly inspired by the seminal work of Fama and French (1993, 2015). While the Fama-French factors are the most widely known, there are more than 100 different factors (or 'anomalies', as the less prominent factors are often dubbed) documented in the literature (e.g., Chen and Zimmermann, 2021; Jensen, Kelly, and Pedersen, 2022). Some large asset managers, such as AQR and Dimensional Fund Advisors, invest in explicit factor-mimicking portfolios or offer products guided by factor premiums,[3] while other fund managers may implicitly pursue factor investing.

This paper examines how transition risk affects factor/anomaly portfolios. In essence, factor investing involves sorting stocks into portfolios based on some observable firm characteristics that are related to the cross section of future stock returns. Some of those characteristics may be correlated with carbon emissions and, consequently, carbon transition risk exposures. We find this to indeed be the case; many quintessential portfolios are heavily weighted toward the highest-emitting firms, while others avoid them. For instance, value-type strategies, irrespective of how 'value' is defined, are disproportionately invested in heavy

[1]For instance, in December 2024, the Governor of New York signed a bill into law to fine fossil fuel companies a total of $75 billion over the next 25 years to pay for damage caused to the climate. See, *New York Times* (December 26, 2024), "Hochul signs law that penalizes companies for greenhouse gas emissions" by Hilary Howard.

[2]See, for example, Bolton and Kacperczyk (2021); Giglio, Maggiori, Rao, Stroebel, and Weber (2021b); Pástor, Stambaugh, and Taylor (2022); Bolton and Kacperczyk (2023); Sautner, Van Lent, Vilkov, and Zhang (2023b); Aswani, Raghunandan, and Rajgopal (2024); Bolton and Kacperczyk (2024); Zhang (2024), and a detailed review of the empirical literature in Giglio, Kelly, and Stroebel (2021a) and Eskildsen, Ibert, Jensen, and Pedersen (2024).

[3]As of June 2024, AQR and Dimensional Fund Advisors had $132 billion and $740 billion in assets under management, respectively.

emitters (e.g., around 35% of the market capitalization of the Fama and French 'Big Value' portfolio is typically composed of heavy emitters). In contrast, growth-focused strategies tilt away from heavy emitters (e.g., only around 5% of the Fama and French 'Big Growth' portfolio is usually composed of heavy emitters).

Given the substantial and persistent prevalence of heavy emitters in value strategy portfolios and consistent data coverage, we examine Fama-French Value portfolio constituents to determine whether investors are differentially compensated for holding these brown firms. Specifically, we split the Big Value portfolio into heavy- and light-emitter stocks. This comparison enables us to study firms with similar key characteristics but significant differences in pollution levels. We find that both the Big Value heavy-emitter and light-emitter portfolios earned roughly similar realized returns - both raw and risk-adjusted - from 2005 to 2023, with the return spread between these two portfolios linked to aggregate commodity prices. Consequently, the heavy-emitting Value portfolio outperformed the light-emitter portfolio during commodity price booms, such as the high inflation period of 2021/2022. However, examining the Implied Cost of Capital (ICC), computed using the average of four different methods, we find no persistent differences between the ICCs of the Big Value heavy-emitter and light-emitter portfolios, except for a brief period between 2017 and 2020, when the average ICC of heavy emitters was temporarily higher. These findings indicate no additional compensation for the potentially higher transition risk faced by heavy-emissions Value firms relative to their light-emissions counterparts.[4] In other words, within the Value universe, there is little evidence of 'brownium' (i.e., that the expected returns of heavy emitters consistently exceed those of light emitters).[5]

We also examine the difference in realized and expected returns between the Big Value and Big Growth light emitter portfolios. This comparison allows us to study firms with similar average 'greenness' but differing in fundamental characteristics, allowing us to infer whether observed patterns in returns could be driven by differences in green credentials. In line with the known outperformance of growth stocks over the last decade, we observe that Big Growth light emitters had higher realized returns (and risk-adjusted returns) than Big Value light emitters during our sample period. Notably, we find that the Big Growth light-emitter portfolio has a consistently lower ICC than the Big Value light emitter portfolio, with the spread significantly widening in recent years as the ICCs of Growth firms decreased.

[4]Alternatively, though unlikely, the market may perceive that heavy emissions do not contribute to greater transition risk for these Value firms.

[5]This finding is consistent with arguments in Berk and Van Binsbergen (2025) and Jagannathan, Kim, McDonald, and Xia (2024) who show that the expected return on brown firms minus that for green firms can be zero when the activist population is below a threshold.

Importantly, using an extensive set of measures, we show that these portfolios do not, on average, meaningfully differ in their level of 'greenness.' Our findings thus call into question the view that the outperformance of growth stocks over value stocks in recent years is mainly driven by growth stocks being predominantly green and investors' preference for greenness rising (lowering) the return investors need for holding brown (green) stocks. Another possible explanation is that the process of creative destruction through new technological advances has simply benefited newer, growing firms at the expense of older incumbents.

We begin our analysis by identifying who the heavy emitters are. Using a comprehensive sample of CRSP firms from 2016 to 2023, coupled with firm-level emissions data, we examine the distribution of emissions among U.S. publicly listed firms. We focus on Scope 1 emissions, i.e., emissions from direct production, as it is a simple, intuitive, and transparent measure that avoids double counting.[6] Together, the Scope 1 emissions of the firms in our sample represent approximately a quarter of the U.S.'s total annual emissions, a quantity that is economically meaningful. Each year, we sort the firms in our sample by carbon intensity (emissions scaled by revenue). We find that the distribution of carbon intensities is highly skewed, with values decaying rapidly as one moves down the list of the most carbon-intensive firms, and the marginal carbon intensities of the bottom half of the sample being economically very similar. Importantly, we find that just 10% of the most carbon-intensive firms (around 300 firms) are responsible for 92% of the aggregate absolute Scope 1 emissions of U.S. publicly listed firms. In fact, only 100 of these firms account for over 80% of aggregate emissions. In other words, the marginal contribution to aggregate direct emissions from firms outside the top decile or quintile of emitters is arguably negligible, regardless of whether a firm falls in the 25^{th} or 90^{th} percentile of carbon intensity.

Given the distribution of carbon intensities and absolute emissions, the top 10% of the most carbon intensive firms stands out in their exposure to potential transition risks. We, thus, classify these firms as heavy emitters (brown firms) because they are not only relatively inefficient with their emissions (i.e., have a high carbon intensity), but they are also the largest absolute polluters.[7] While these firms are primarily from known heavy-emitting industries such as Utilities, Energy, and Transport, our procedure identifies the largest emit-

[6]Our list of the most salient heavy emitters is not materially affected when considering the sum of Scope 1 emissions and Scope 2 emissions (emissions associated with the energy the firm buys and uses), or the sum of Scope 1, 2, and upstream Scope 3 emissions (emissions that are not produced by the company itself, but are part of its value chain).

[7]The exact cutoff of 10% is immaterial to our main conclusions, as similar results are observed with different cutoffs. However, firms beyond this threshold have marginal carbon intensities and contributions to aggregate emissions that are minimal compared to the top 10% of the most carbon-intensive firms.

ters irrespective of their industry. As we elaborate below when validating our classification, the only notable omission of our simple method is that it does not categorize manufacturers of internal-combustion engine vehicles like Ford and GM as heavy emitters, even though these firms are clearly exposed to transition risk due to their substantial downstream (final consumer) emissions.[8] To address this concern, we include five manufacturers of internal combustion engines and vehicles (Ford, GM, Paccar, Caterpillar, and Cummins) in our set of heavy emitters, replacing the five least carbon-intensive firms within the top 10% of carbon-intensive firms.[9]

We validate our classification of heavy emitters using three methods. First, we assess the persistence of heavy emitter categorizations over time and find them to be highly persistent; once a firm falls into the top 10% of carbon-intensive firms in a given year, there is a 93% probability that it will remain in that category the following year. Second, we confirm our classification by cross-referencing it with environmental (E) scores from MSCI, finding high correlations: the heavy emitters have the lowest E scores. Third, we compare our list of heavy emitters with those identified by the Climate Action 100+ investor-led initiative and the London School of Economics (LSE) Transition Pathway Initiative (TPI) Centre, finding that our classification aligns very closely with the assessments of these external sources.

We posit that studying these heavy emitters is essential as they are the firms most vulnerable to the challenges posed by the carbon transition. Potential adverse impacts may arise from a combination of sources, including (i) technological advancements, (ii) government actions (regulations, subsidies/penalties, etc.) (iii) investor divestment (and lending restrictions), and (iv) consumer-driven actions (e.g., boycotts). The most significant emitters are likely to draw increased scrutiny from investors, consumers, and regulators. Furthermore, implementing substantial operational changes to reduce emissions could be prohibitively expensive and inefficient for these firms. Consequently, heavy emitters are particularly susceptible to transition risk.[10] The U.S. coal industry's experience serves as a tangible example of how these forces can converge, leading to industry-wide adverse impacts from technological shifts, stringent regulations, divestment efforts, and consumer boycotts (see, e.g., Bassen, Kaspereit, and Buchholz, 2021; Scott, 2020).[11] In fact, the decline of the U.S. coal industry

[8]For example, the Climate Action 100+ initiative (discussed later) includes the five internal-combustion engine and vehicle manufactures in their list of most climate transition risk sensitive firms.

[9]Including or excluding these five firms does not materially affect our results; however, we choose to include them in our benchmark classification for a more intuitive and consistent exposition.

[10]This is also reflected in the findings of Ilhan, Sautner, and Vilkov (2021), who report that the costs of option protection against climate-related downside tail risk are higher for carbon-intensive companies.

[11]Welsby, Price, Pye, and Ekins (2021) estimate that 97% of technically and economically proven coal

continued even under President Trump's first administration, despite his highly favorable stance toward it (Jagannathan, Ravikumar, and Sammon, 2018).[12] Given these issues, it is crucial for investors to understand how their portfolios are exposed to these firms.

Having established our list of heavy emitters, we explore the types of portfolios in which heavy emitters typically fall. Pástor et al. (2022) provide some evidence suggesting that value strategies may tilt toward brown firms, as their time series regression of their green-minus-brown factor on the Fama-French factors shows a significant negative exposure to Fama-French's HML factor. We take a different approach and, in the spirit of Daniel and Titman (1997), examine the exact composition of characteristic-sorted portfolios. We begin with the Fama-French portfolios, given their widespread use in the profession and their ability to capture a broad spectrum of available strategies, while also examining a comprehensive list of alternative portfolios from the literature. Our goal is to assess the prevalence of heavy emitters within a broad set of characteristic-sorted portfolios.

Examining the market capitalization share of heavy emitters in Fama-French portfolios, we observe a few notable patterns. First, we note that although heavy emitters are responsible for nearly all the emissions of listed firms, they represent only 12% of the aggregate market capitalization. Then, starting with the two size-sorted portfolios, we note that heavy emitters are more prevalent in the Big portfolio than in the Small portfolio, representing, on average, 13% and 8% of portfolio value, respectively (a pattern consistent with the fact that heavy emitters tend to be larger and older firms). Turning to the book-to-market-sorted portfolios, we observe the starkest patterns. Specifically, heavy emitters represent, on average, 37% of the value of Big Value portfolio and only 3% of the Big Growth portfolio, with this difference being highly statistically significant and consistent over time. Additionally, we observe a significant difference in the concentration of heavy emitters between the Small Value and Small Growth portfolios, although the difference is economically smaller, with 14% of heavy emitters in Small Value and 4% in Small Growth. These pattern also hold when examining simple firm counts rather than market capitalization shares.

It is important to note that, by construction, our set of heavy emitters comprises 10% of the sample of firms (12% in terms of market capitalization). Therefore, if there were no relationship between being a heavy emitter and the characteristic on which the portfolios

reserves would be stranded in a scenario to limit global warming to 1.5°C degrees above pre-industrial levels.

[12]Coal-fired power generation in the U.S. declined by 38% during the first Trump administration (EIA, 2024). At the peak of electricity production from coal in the U.S. in 2007 (2,016 billion kilowatt-hours), coal accounted for almost half of the electricity generation (48.6%). The share of electricity generation from coal has since steadily dropped to 16.7% in 2023. Over the same period, the fraction of electricity production from renewable energy sources increased from 8.5% to 21.4% (EIA, 2024).

are sorted, we would unconditionally expect to see an average share of approximately 10% of firms (12% by value) in each portfolio. Even considering the conditional share of heavy emitters in the Big portfolio at around 13%, their share in the Big Value and Big Growth portfolios is almost three times bigger and over three times smaller, respectively, than would be expected. We further validate these observed patterns in the Fama-French book-to-market-sorted portfolios by examining the holdings of two exchange-traded funds (ETFs): the Vanguard Value Index Fund ETF (VTV) and the Vanguard Growth Index Fund ETF (VUG). Between 2016 and 2022, we find that VTV held, on average, 21% of its portfolio in heavy emitters, while VUG held only 4%, with these shares remaining extremely stable over time.[13] Hence, we find that value investing is associated with significant heavy emitter exposure, whereas Growth investing largely avoids such exposure. Conversely, our results also show that not all of the Value portfolio is comprised of brown firms, a key fact that we exploit when examining returns.

Examining investment-sorted portfolios, we do not find pronounced differences between the long leg (Conservative investment) and the short leg (Aggressive investment) of the strategy. Although heavy emitters are somewhat more prevalent in the Conservative portfolio and less so in the Aggressive portfolio during our sample period, these differences are minor and change sign over time. This can be attributed to the cyclical nature of investments among heavy emitters, which respond sharply to changes in commodity prices and frequently shift between portfolios. In contrast, we find an economically meaningful difference among profitability-sorted portfolios. Heavy emitters are significantly over-represented in the Big Weak profitability portfolio, with a 29% share of market capitalization on average, and under-represented in the Big Robust profitability portfolio, with only a 7% share. However, when examining the share in terms of the number of firms, the share of heavy emitters in the Big Weak portfolio decreases to 16%. Another caveat is that this pattern reverses among small stocks, where heavy emitters are more prominent in the profitable portfolio and less so in the unprofitable portfolio; however, the absolute shares are economically small. Our results suggest that sorting large stocks by profitability may inadvertently reduce transition risk, while doing the same for small stocks may increase it. Lastly, as a placebo test, we analyze momentum-sorted portfolios. Due to the high turnover of momentum portfolios, we expect heavy emitters to be equally likely to appear in any momentum portfolio. As expected, our analysis shows no significant difference in the prevalence of heavy emitters between momentum winner and loser portfolios, underscoring their notable presence in other

[13]The Internet Appendix plots these shares over time.

portfolios, such as Big Value.

We also examine 161 anomaly portfolios from Chen and Zimmermann (2021) that we could replicate using our sample and for which we have sufficient coverage. We focus on anomaly portfolios related to value, investment, and profitability themes to reinforce our main findings based on Fama-French portfolios. Analyzing more than a dozen value strategies, including those based on intangible returns, cash productivity, enterprise multiples, sales-to-price ratios, and dividend yields, we consistently find that heavy emitters are predominantly present in the long leg (value portfolios) and are significantly underrepresented in the short leg (growth portfolios). Thus, the tilt of value strategies toward heavy emitters remains consistent regardless of how 'value' is defined. Similarly, we find comparable results using alternative investment measures, where the share of heavy emitters is slightly higher among low investment portfolios, though these shares fluctuate over time. Consistent patterns also emerge when using different profitability measures, such as cash-based operating profitability, where heavy emitters are significantly over-represented in the low-profitability (short-leg) portfolios. Thus, this analysis corroborates all our benchmark findings.

We observe no significant differences in the concentration of heavy emitters in most anomaly strategies. For example, expectedly, we find no differences among alternative versions of momentum strategies or other returns-based, high-turnover strategies. However, we identify some additional notable patterns. Specifically, heavy emitters are prevalent in the short leg of various strategies with the common theme that the short side is typically unglamorous and lacks financial robustness. For example, heavy emitters often display traits such as low cash-to-assets ratios, high net debt, inconsistent earnings, high cash flow variance, low pension funding status, and low organizational capital. In summary, our findings highlight the significant presence of heavy emitters in various factor and anomaly portfolios, emphasizing the potential transition risks investors may face (or avoid) when following these well-known investment strategies.

Having established that heavy emitters are prevalent in certain prominent characteristic-sorted portfolios, particularly in value strategies, we explore whether investors are, or can expect to be, differentially compensated for their exposure to transition risk through their holdings of these heavy emitters. To this end, we focus on the Fama-French Big Value portfolio, breaking it down into heavy emitters and light emitters (with light emitters defined as those not classified as heavy emitters), and examine their realized and expected returns. For this analysis, we omit firms from the utilities sector, as those firms exhibit fairly different return patterns and have very low market betas relative to other firms, making comparisons difficult. Importantly, the firms in the Big Value heavy-emitter and light-emitter portfolios are, by construction, matched on key characteristics: similar size and book-to-market ratios, and, in our sample, they also exhibit similar market beta. However, they differ significantly in their emissions intensities and absolute emissions.

When examining their realized returns (either raw or risk-adjusted using the Fama-French factors), we find no statistically significant differences in average returns between the two portfolios. For instance, the cumulative returns from 2005 to 2016 (around the Paris Agreement) and from 2005 to 2020 were nearly identical for the light and heavy emitter Big Value portfolios. While there were periods when the heavy-emitter Value strategy outperformed the light-emitter Value strategy, these instances were typically associated with temporary favorable changes in expected future cash flows driven by commodity price booms, such as during the recent inflationary period of 2021-2022, particularly after the onset of the Russia-Ukraine war. Importantly, when examining the ICC, we find no statistically or economically significant persistent differences between the ICC of the Big Value heavy-emitter and Big Value light-emitter portfolios, except for a brief period between 2017 and 2020. Our results suggest that investors do not typically anticipate higher returns (relative to low-emitter Value stocks) for holding heavy emitters and bearing greater transition risk.

In stark contrast, we find a strongly significant and highly persistent difference in ICC between the light-emitter Big Value portfolio (representing around 60% of the Big Value portfolio) and the light-emitter Big Growth portfolio (representing around 95% of the Big Growth portfolio), amounting to around 2.3% per year on average, and significantly widening to around 3.6% since 2016, a period that coincided with the outperformance of growth stocks. Notably, we find that while these two portfolios command significantly different costs of capital, firms in the light-emitter Big Value portfolio are arguably as 'green' as those in the light-emitter Growth portfolio, exhibiting very similar value-weighted and equal-weighted emission intensities (irrespective of whether we consider solely Scope 1 emissions or the sum of all three Scopes), absolute emissions, and E scores. These results suggest that the lower cost of capital of growth stocks and their recent outperformance relative to value stocks is unlikely to be primarily driven by differences in their 'greenness.'

Related literature The 2022 American Finance Association presidential address emphasized that the finance research community has both the ability and the responsibility to address critical questions related to sustainable finance (Starks, 2023). Pedersen (2023) argues that green finance is crucial for decarbonization in the absence of regulation. The concern that heavy emitters pose a unique and significant risk extends beyond the finance literature, particularly due to their potential for substantial losses during carbon transitions.[14]

Our research contributes to three strands of the literature. First, we relate to the literature that uses portfolio returns to estimate factor exposure and portfolio decarbonization (see, e.g., Madhavan, Sobczyk, and Ang, 2021; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2021; Bolton, Kacperczyk, and Samama, 2022). More generally, we contribute to the extensive literature on stock market factors (see, e.g., Fama and French, 1993, 2015; Asness, Frazzini, Israel, and Moskowitz, 2015), particularly recent studies that consider all factors together (e.g., Hou, Xue, and Zhang, 2020; Chen and Zimmermann, 2021; Jensen et al., 2022). Our research differs from existing studies in that we examine the precise composition of characteristic-sorted portfolios that have been highlighted as significant in the existing literature rather than relying on indirect measures like correlations. In addition, we focus on the effect of heavy emitters on factor and anomaly portfolios.

Second, we relate to theoretical work that shows that brown firms should command a premium (Heinkel, Kraus, and Zechner, 2001; Pástor et al., 2021; Pedersen et al., 2021), either due to investors' increased demand for green assets or because brown stocks are more exposed to carbon transition risks, as argued by Bolton and Kacperczyk (2023).

Third, we relate to the empirical work on the performance of brown versus green firms (e.g., Bolton and Kacperczyk, 2021; Pástor et al., 2022; Bolton and Kacperczyk, 2023; Sautner et al., 2023b; Aswani et al., 2024; Zhang, 2024), offering a unique portfolio-level perspective. Empirical evidence on the performance of green versus brown stocks is mixed. Eskildsen et al. (2024) offer an exhaustive and recent overview of studies reporting positive, negative, or no differences in past performance.[15] Additionally, the authors find that replicating previous studies using an extended sample period reverses some of the original results. Given the short sample period of pollution and E scores data, and the potential for a regime shift after the Paris Agreement, ex post realized returns may be unreliable estimates of expected returns. Thus, we rely on ICC measures (Gebhardt, Lee, and Swaminathan, 2001; Claus and Thomas, 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005; Mohanram and Gode, 2013) and contribute to the literature that analyzes the performance of polluting firms using various ICC definitions, such as in Pástor et al. (2022) and Eskildsen et al. (2024). Pástor et al. (2022) estimate substantially lower expected returns for green stocks than for

[14] See, for example, Griffin, Jaffe, Lont, and Dominguez-Faus, 2015; Trinks, Scholtens, Mulder, and Dam, 2018; Semieniuk et al., 2022.

[15] Giglio et al. (2021a) review the earlier empirical literature studying the pricing of climate risks across different asset classes.

brown stocks using ICC. Eskildsen et al. (2024) propose a different green score specification and conclude that green stocks have lower expected returns than brown stocks, although the difference is much smaller than in Pástor et al. (2022). While these studies analyze brown and green portfolios, we focus on the top 10% of heavy greenhouse gas emitters within the CRSP universe, which account for the majority of Scope 1 emissions in our sample. We find that within Big Value, the implied cost of capital does not differ between heavy and light emitters. However, significant differences in expected returns persist between Growth and Value portfolios, regardless of how 'brown' the Value portfolio is.

2 Data

We primarily use three databases: Center for Research in Security Prices (CRSP) for price and return data, Compustat for firm fundamentals, and S&P Global Trucost (Trucost) for firm emissions. For certain analyses, we also use E scores from MSCI and retrieve the lists of firms tracked by Climate Action 100+ and the LSE Transition Pathway Initiative (TPI) Centre from their respective websites.[16]

We select all companies covered in the CRSP monthly U.S. stock database, which includes stocks traded on the NYSE, Amex, and Nasdaq, and match firm characteristics from Compustat with GHG emissions data from Trucost. Following Fama and French (2015), we use only NYSE, AMEX, and NASDAQ stocks from both CRSP and Compustat that have share codes 10 or 11. CRSP monthly returns are adjusted for delistings.

We use the CRSP/Compustat Link table to retrieve the company GVKEY for each PERMNO and match it to Compustat data. To match the primary identifier in Trucost (Company ID) to firms' PERMNO, we use the 'Identifiers' table in Capital IQ, available in WRDS.[17] For descriptive statistics, when reporting the number of companies, we use unique PERMCOs in CRSP and aggregate market capitalization for firms with multiple PERMNOs (e.g., firms with dual share classes). The analysis of factor and anomaly portfolios is conducted at the security level, as is standard in the asset pricing literature.

Trucost provides data on absolute Scope 1, Scope 2, and upstream Scope 3 emissions, as well as the corresponding carbon intensities. Trucost sources the information from publicly disclosed company financial reports (annual reports, financial statements, 10-K/20-F reports, SEC/regulatory filings), environmental data sources (corporate social responsibil-

[16]See www.climateaction100.org and www.transitionpathwayinitiative.org, respectively.

[17]Some GVKEYs in Trucost are assigned at the beginning of data coverage and are not updated thereafter.

ity, sustainability, or environmental reports, the CDP, EPA filings), and company websites (Global, 2020). For Scope 2, we consider the numbers assessed by a location-based approach that uses the average intensity of the electricity grid to calculate carbon emissions, as this measure has the best data coverage.[18]

The ICC estimates using four different methodologies (Claus and Thomas, 2001; Gebhardt et al., 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005) are from Eskildsen et al. (2024). For the construction of anomaly portfolios, we use the signals (that utilize CRSP or Compustat data) for 209 anomalies from Chen and Zimmermann (2021).[19]

2.1 Emissions data coverage

The Internet Appendix shows Trucost emissions data coverage. Starting in fiscal year 2005, Trucost covered 843 CRSP firms. Coverage expanded in 2016 to include mid- and small-cap companies.[20] We observe an increase in the number of firms covered, from an average of 23% of the CRSP sample during 2005-2015 to 69% during 2016-2023. In terms of market capitalization, coverage was already at 87% from 2005 to 2015, before expanding to 99% in 2016 and beyond. Since some of the factor portfolio analysis involves equally weighted subsamples, good coverage is important for both the number of firms and market capitalization. Therefore, our main analysis uses the sample period starting from 2016 onward.

3 Identifying heavy emitters

In this section, we describe the distribution of GHG emissions among publicly listed U.S. firms and present a simple, robust method for identifying the most salient heavy emitters.

3.1 Classification of heavy emitters

Previous studies typically rely on industry-based classification guided by the IPCC's categorization of heavily polluting industries (see, e.g., Choi, Gao, and Jiang, 2020). Although

[18]Scope 2 data from the market-based approach, which uses contractual agreements between companies and energy suppliers to calculate carbon emissions, has only been available in Trucost since 2021, and is reported by only 40% of companies (Swinkels and Markwat, 2023).

[19]www.openassetpricing.com

[20]Some limited data is available prior to 2005, starting in July 2002 and gradually increasing from 405 firms included in CRSP in 2002, to 611 firms in 2003, and 736 firms in 2004. We exclude data for these initial years, as the number of covered firms is only 11% over this period. Moreover, Trucost officially states that historical coverage for large-cap companies begins in 2005.

heavy polluters tend to be concentrated in just a few industries, industry-based classification is, by its nature, coarse (for example, not all utility firms are equally polluting). Therefore, we use firm-level emissions data to categorize each firm.

Our analysis requires identifying the heaviest emitters, as these firms are most likely to be adversely affected by the carbon transition. For our primary analysis, we focus exclusively on Scope 1 emissions – direct GHG emissions under the firm's control – as this measure is intuitive, keeps our analysis parsimonious, and avoids double counting (for example, the Scope 2 emissions of a firm from purchased electricity are the Scope 1 emissions of the utility or energy provider generating that electricity).

Although emissions from Scope 2 and upstream Scope 3 provide valuable information, they are less relevant for our analysis.[21] Nevertheless, it is important to note that our main empirical results are largely unaffected by the choice of emissions measure used to classify heavy emitters. Whether we use Scope 1 emissions alone, the combined total of Scope 1 and 2 emissions, or the sum of Scope 1, 2, and upstream Scope 3 emissions, essentially the same set of firms is generally identified as the heaviest emitters. The overlap of heavy emitters identified using only Scope 1 emissions, the sum of Scope 1 and 2, or the sum of Scope 1, 2, and 3 emissions is 93% and 80%, respectively. Any differences in classification do not significantly impact the tails of the distribution, which is the primary focus of our analysis.

To classify each firm, we utilize a commonly used measure in practice: carbon intensity, defined as the firm's Scope 1 GHG emissions (measured in metric tons of carbon dioxide equivalent) per $1 million in revenue (mt$CO_2e/USM). Aswani et al. (2024) and Zhang (2024) persuasively argue that carbon intensity is the most appropriate measure to assess carbon performance. While larger firms, much like larger countries, inevitably pollute more, it is also crucial to consider how efficiently the firm (or country) manages its carbon emissions. Carbon intensity measures how efficiently a firm operates relative to its pollution levels. We believe this measure aligns well with our objective of identifying firms most likely to be adversely affected by carbon transition risk. We can imagine that the most carbon-intensive

[21] Upstream Scope 3 emissions, for example, capture indirect emissions from a company's supply chain. Firms with high upstream Scope 3 emissions may face less severe impacts from carbon transition risk, as they can mitigate emissions by substituting brown suppliers with greener ones, potentially without incurring significant costs. Similarly, industries with high upstream Scope 3 emissions, like retail, are less likely to face immediate regulatory scrutiny or divestment pressures compared to firms with direct emissions. Thus, the link between high emissions and adverse exposure to carbon transition risk is less clear for these firms. Additionally, upstream Scope 3 emissions often involve significant double counting. For instance, food processors typically report high upstream Scope 3 emissions due to their supply chains, which overlap with direct emissions from the transportation sector. Furthermore, Scope 3 reporting is not standardized and is often incomplete, leading to measurement errors.

firms (the least carbon-efficient) would be among the first to attract regulatory, consumer, and investor attention, incur substantial costs in the event of material carbon taxes, or potentially be most disrupted by new technologies.[22] Importantly, our approach of sorting based on carbon intensity also captures the largest absolute emitters.

Specifically, each year we sort firms in our sample based on its carbon intensity. To help visualize the process, Figure 1 shows the average dispersion of carbon intensity within each industry. We use the Fama-French 12 industries classification, which is widely utilized in asset pricing literature, making our results more easily comparable to existing studies.[23] We, however, make four adjustments to the industry classification. First, we separate Agriculture from Non-Durables because it is one of the most carbon-intensive sectors (Crosignani, Osambela, and Pritsker, 2024).[24] Second, we subdivide the Other category of the original 12-industry classification into four additional industries: Mining, Transportation, Construction, and Hotels and Entertainment, with the residual 'Other' containing firms that do not fall into these four sectors. We split the Fama-French Other category because, over the period 2016–2023, it accounts for approximately 20% of overall Scope 1 emissions, making it the third most significant sector in terms of GHG emissions, behind only the Utilities and Energy sectors.[25] Third, we report Berkshire Hathaway (BRK) separately due to its

[22]To use a country example, while Australia is far from being the largest absolute emitter, its very high per capita emissions (ranking third globally and first among the G20 in GHG emissions per capita) have forced it to make substantial changes in recent years. See, Reuters (January 18, 2024), "Australia cleans up at home, but exported emissions keep growing" by Gavin Maguire.

[23]The Fama-French 12 industries are as follows: Consumer Non-Durables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Energy (Enrgy), Chemicals (Chems), Business Equipment (BusEq), Telecommunications (Telcm), Utilities (Utils), Shops (Shops), Healthcare (Hlth), Finance (Fin), and Other. Given that we consider only publicly-listed U.S. firms, several key sectors essential for achieving net zero are underrepresented among publicly traded firms. Specifically the Agriculture, Forestry, and Other Land Use (AFOLU) and buildings sectors. The IPCC estimates that the AFOLU sector accounted for 13-21% of global total anthropogenic GHG emissions during the period 2010-2019.

[24]'Agricultural production - crops' (SIC codes 0100-0199), 'Agricultural production - livestock' (SIC codes 0200-0299), and 'Agricultural services' (0700-0799).

[25]To assign companies to the first three industries, we use the Fama-French 17 industries classification. For the hotels and entertainment sector, we compile our own list of SIC codes from the Other category (the SIC codes for the hotels and entertainment are in the range 7830-8800). Additionally, we reclassify a few SIC codes that have been assigned to one of the 12 Fama-French industries. 'Bituminous coal' (SIC 1200-1300) and 'Wholesale – metals and minerals' (SIC 5050-5053) are reclassified from 'Energy' and 'Shops', respectively, to 'Mining' following the Fama-French 17 industries classification. Similarly, 'Miscellaneous transportation equipment' (SIC 3799) is reclassified from 'Manufacturing' to 'Transportation'. For the additional industry 'Construction', 'Paints' (SIC 2850-2860) is reclassified from 'Chemicals', and products such as stone, concrete, and glass (select SIC codes in the range 3200-3300) and tools, heating equipment, plumbing fixtures, and prefabricated metal or lumber products (select SIC codes in the range 3420-3453) from 'Manufacturing'. Retail and wholesale of these products (SIC codes in the range of 5030-5252) are also reassigned from 'Shops' to 'Construction'.

large emissions, which would otherwise inflate our newly defined Other category. Fourth, we report the statistics for the so-called FAAMG firms (Facebook/Meta, Amazon, Apple, Microsoft, and Google/Alphabet) separately, as these firms represent a significant share of the aggregate market capitalization in recent years.[26] The box of each plot delimits the quartiles of the carbon intensity distribution, the line across the box shows the median, and the whiskers extending from below and above the box delimit the 2.5^{th} and 97.5^{th} percentiles.

The Utilities sector contains firms with the highest carbon intensities, followed by the Mines and Chemicals sectors in second and third place, respectively. As we begin sorting firms from highest to lowest carbon intensities, we initially include only Utilities firms. However, firms from the Mines and Chemicals sectors are quickly added, followed by the most carbon-intensive firms from the Agriculture and Manufacturing sectors, before we include any firms from the Energy sector. In other words, our approach ensures that we add the most carbon-intensive (i.e., the most 'brown') firms first, irrespective of their sector allocation.

Figure 2 plots the marginal carbon intensity of the top $x\%$ of firms ranked by their carbon intensity. We observe an exponential decrease in carbon intensity as one moves from the most carbon-intensive firms to the least. For instance, the marginal carbon intensity of the top 1%, 5%, and 10% most carbon-intensive firms is 38.10, 4.87, and 1.79 mtCO_2e/US\$M, respectively, whereas the marginal carbon intensity of the top 20%, top 50%, and bottom 20% drops to 0.32, 0.13, and 0.01 mtCO_2e/US\$M, respectively. Given that a typical passenger vehicle emits about 4.6 mtCO_2e per year[27], the carbon intensities of firms below the top decile or quintile of the most carbon-intensive firms are, in economic terms, arguably negligible.[28] Therefore, the most carbon-intensive firms stand out as unique in their emission intensities.

However, from an economic perspective, absolute emissions—not just relative emissions—may be what truly matters. Hence, having sorted firms from highest to lowest carbon intensity, we investigate the share of total GHG emissions accounted for by the firms with the highest carbon intensities.

Figure 3(a) shows the percentage of total GHG emissions from U.S. public firms accounted for by the top $x\%$ of carbon-intensive firms. The line initially increases steeply before flattening out significantly after about the top 10% of the most carbon-intensive firms. Figure 3(b) provides the exact numbers for a few key cutoffs (the top 5%, 10%, 15%, and 20%). We

[26]According to the Fama-French 12 industry classification: Facebook/Meta, Apple, Microsoft, and Google are classified as Business Equipment, while Amazon is classified as Shops.

[27]See, www.epa.gov/greenvehicles/greenhouse-gas-emissions-typical-passenger-vehicle.

[28]Hartzmark and Shue (2023) also point out that for firms with low levels of emissions, percentage reductions in emissions are economically trivial. They show empirically that the focus on percentage reductions provides very weak financial incentives for heavy emitters to become more green.

observe that the top 5% of the most carbon-intensive firms alone account for a staggering 69.8% of the total Scope 1 GHG emissions of U.S. publicly listed firms, while the top 10% and 15% account for approximately 92.1% and 94.8% of total GHG emissions, respectively.

Surprisingly, even though we sort firms by their carbon intensities, our procedure still identifies those that contribute the most to aggregate absolute GHG emissions. This pattern further supports the notion that the heaviest emitters are most likely to be disproportionately affected by transition risk. Not only are they the least efficient, but they also contribute the vast majority of absolute emissions, whereas the contributions from other firms are negligibly small. As we pointed out earlier, the slope of the line in Figure 3 drops sharply. Specifically, the marginal five percent of firms, when moving from the top 10% to the top 15% of carbon-intensive firms, only represent about 2.7% (the difference between 92.1% and 94.8%) of aggregate GHG emissions. Interestingly, while these firms represent a disproportionate share of total GHG emissions, their share of total market capitalization is largely commensurate with their quantity. For instance, the top 5% and 10% most carbon-intensive firms account, on average, for 5.5% and 12.3% of aggregate market capitalization, respectively.

Figure 4(a) displays total GHG emissions by industry for the top-emitting firms sorted by carbon intensity, offering an alternative perspective to the pattern shown in Figure 3. We find that the top 10% of carbon-intensive firms account for the majority of emissions across all major high-emitting industries. For instance, they contribute 99% of emissions in the Energy and Utilities sectors, 94% in Transportation, and 85% in Manufacturing (percentage contributions are plotted in the Internet Appendix). Notably, Figure 4(b) shows that in many sectors, while a few heavy emitters account for the majority of pollution, they do not represent significant shares of sector market capitalization. For instance, in Manufacturing, the top 10% of the heaviest emitters account for 85% of GHG emissions but represent only about 15% of the sector's market capitalization.

Heavy emitters definition In light of the observed patterns discussed above, we define the top 10% most carbon-intensive firms as our group of heavy emitters.[29] Based on the validation of our list of heavy emitters against external sources (discussed below), we make one adjustment: we replace the five least carbon-intensive firms with five manufacturers of internal combustion engines (Ford, GM, Caterpillar, Paccar, and Cummins).[30]

[29] We also confirm that all our main results remain quantitatively similar when using a cutoff of the top 5% or top 15%. These results are available upon request.

[30] Whether these five firms are included or excluded does not materially impact our results; however, we include them in our benchmark classification to provide a more intuitive exposition.

Largest absolute emitters The pronounced pattern in Figure 3 can be explained by the fact that a small fraction of firms is responsible for the majority of emissions. The Internet Appendix illustrates the distribution of average Scope 1 emissions within each industry, showing that several industries are dominated by a few major emitters. For example, we observe a pronounced concentration in the Energy sector. Specifically, while there were on average about 95 publicly listed firms in the Energy sector, at the end of 2023, Exxon alone constituted 29.2% (109.0 million metric tons of CO_2e) of the sector's aggregate Scope 1 emissions, followed by Chevron and Marathon Petroleum, which together account for an additional 23.2%. A similar pattern is observed in other top-polluting sectors, such as Utilities, Transport, Chemicals, and Manufacturing. For instance, in the Utilities sector, which comprises around 77 publicly listed firms, at the end of 2023 four companies (Vistra, Southern, Duke Energy, and American Electric Power) dominate with a combined share of 37.6% (309.6 million million metric tons of CO_2e) of the industry's aggregate Scope 1 GHG emissions. Exploiting this fact, we slightly adjust our procedure to identify the most salient emitters in our set of heavy emitters. Specifically, we begin with the top 10% of heavy emitters (typically around 300 firms), and then sort these firms by their aggregate emissions. While not strictly relevant for our purposes, as we aim to identify all the heavy emitters, this exercise yields some interesting results. In the Internet Appendix, we plot the cumulative fraction of aggregate GHG emissions for these firms. This analysis reveals that a small number of larger firms among the heavy emitters are responsible for most of the aggregate emissions. Specifically, the three largest GHG emitters over the period 2016–2023 account, on average, for 14.9% of the aggregate GHG emissions of the CRSP sample.[31] Notably, we find that just 100 firms account for 86% of the aggregate GHG emissions in our sample. These findings are consistent with Heede (2014) and the 2024 report by the Carbon Majors Database, which shows that over 70% of global CO_2 emissions historically can be attributed to just 78 corporate and state entities.[32] Similarly, a 2019 report by *The Guardian* finds that 20 entities are responsible for a third of worldwide carbon emissions, with Exxon, Chevron, and ConocoPhillips, three firms in our sample, among the 20 biggest polluters.[33]

[31]In recent years, the three largest emitters were Exxon Mobil, Vistra, and Southern.

[32]See https://carbonmajors.org/briefing/The-Carbon-Majors-Database-26913.

[33]*The Guardian* (October 9, 2019), "Revealed: the 20 firms behind a third of all carbon emissions" by Matthew Taylor and Jonathan Watts.

3.2 Validating the classification of heavy emitters

We validate our choice of heavy emitters in three ways. We examine the persistence of heavy emitter categorizations, we confirm our categorization using E scores, and we compare our list of heavy emitters to that of the Climate Action 100+ initiative and to that of the LSE Transition Pathway Initiative (TPI) Centre. We also present a case study of Eversource Energy, a utility company, to demonstrate the flexibility of our approach and the limitations of industry classification. Lastly, based on the insights from the validation exercise, we discuss some of the limitations of our approach.

3.2.1 Persistence of heavy emitters

For our characterization of heavy emitters to be meaningful, firm categorizations must be persistent. If a firm is a heavy emitter one year and a low emitter the next, it suggests the firm can easily reduce its emissions, undermining the argument that it is significantly exposed to carbon transition risk. To verify if this is the case, we analyze the persistence in carbon-intensity rankings.

Figure 5 illustrates the persistence in carbon-intensity rankings. Each year, we assign firms to deciles based on their carbon intensity, with decile 1 containing the firms with the lowest carbon intensity and decile 10 the firms with the highest. We then calculate the transition probability $p(j, i)$ for firms moving from one decile to another between two subsequent years, repeating this calculation for each pair of subsequent years. The figure shows the average transition probabilities over the period 2016−2023. The bars in cell (current, previous) represent the conditional probability of achieving a current ranking of decile j, given a ranking of decile i in the previous year. The bars along the diagonal, representing firms that maintain their decile ranking from one year to the next ($j = i$), clearly stand out, indicating that carbon-intensity rankings are relatively stable over time. Even for deciles 5 and 6, transition probabilities are fairly high (75.8% and 73.6%, respectively), but for the tail deciles, the transition probabilities are particularly elevated. The transition probability of the firms with the lowest carbon intensities in decile 1 is 92.7%, while the probability for the firms with the highest carbon intensities to remain in decile 10 is 96.5%. These heavy emitters have just a probability of 3.1% of moving from decile 10 to decile 9 between two subsequent years, and only a 0.1% chance of dropping to decile 8. This suggests that our categorization is meaningful, as heavy emitters are unlikely to easily transition to being low emitters.[34]

[34]Given the high persistence in carbon-intensity rankings shown in Figure 5, we backfill pollution data

3.2.2 E scores

We verify whether our list of heavy emitters aligns with MSCI's E scores by examining the raw (non-industry-adjusted) standardized MSCI environmental pillar scores (E scores). The raw E scores are calculated by interacting the E pillar scores, which measure a company's resilience to environmental risks on a scale from 0 to 10, with the E pillar weights, which represent the importance of environmental factors relative to social and governance factors within an industry, on a scale from 0 to 100. A higher E score indicates a 'greener' firm.[35]

Table 1 reports the average E scores for the top 10% carbon-intensive firms and the remaining 90%. We find that the E scores of heavy emitters are significantly worse (i.e., more brown) than those of other firms. Specifically, the top 10% most carbon-intensive firms have average standardized E scores of −1.49, more than one standard deviation below the mean, while the other 90% have an average standardized E score of 0.19. There is a significant inverse relationship between carbon intensity and E scores: the higher a firm ranks in terms of carbon intensity, the lower its E score. This relationship is illustrated in Figure 6. These findings confirm that heavy emitters are consistently associated with low E scores. Hence, E scores could potentially identify heavy emitters, as suggested by Pástor et al. (2022). However, we argue that our method is simpler and more transparent, as ESG scores are often criticized for being black-box measures (e.g., Berg, Koelbel, and Rigobon, 2022). Moreover, our data coverage during the sample period surpasses that of MSCI, making our method better suited for this analysis.

3.2.3 Climate Action 100+ firms

To validate whether our list of heavy emitters captures the firms most vulnerable to carbon transition risk, we check if the firms tracked by Climate Action 100+ appear among those identified using our measure. The investor-led initiative Climate Action 100+ aims to ensure the world's largest GHG emitters take necessary actions to limit global warming through direct engagement, investor collaboration, and leveraging shareholder influence to promote better climate practices. Climate Action 100+ focuses worldwide on 170 companies critical

in some analyses. Although market capitalization coverage was already high before 2016, this backfilling significantly increases firm coverage in earlier years. The Internet Appendix shows Trucost data coverage for this backfilled sample.

[35] Raw E score = $-(10 -$ environmental-pillar-score$) \times$ environmental-pillar-weight $/100$. The term in brackets measures the firm's distance from a perfect environmental score of 10, and multiplying by the environmental pillar weight scales this by the firm's exposure to environmental risks within its industry. The negative sign ensures that firms with better environmental performance have higher raw E scores.

to the net-zero emissions transition; of these, 38 firms are part of the CRSP sample. We examine whether these 38 firms are also identified in our list of heavy emitters.[36]

Overall, our method effectively identifies most of the firms vulnerable to carbon transition risks, aligning closely with the assessments of Climate Action 100+. We find that 31 of the 38 Climate Action 100+ firms are among our list of heavy emitters. Specifically, 26 firms fall into the top 10% of firms with the highest carbon intensity, and the other five are car and heavy truck manufacturers (Ford, General Motors, Caterpillar, and PACCAR) and a heavy equipment and automotive company (Cummins) that we also include in our list of heavy emitters.

The eight excluded firms include three aerospace and military hardware companies: Boeing, Lockheed Martin, and Raytheon Technologies. While Boeing, with its large exposure to passenger air travel, could arguably be included in our list of firms most exposed to transition risk due to its high emissions, it is doubtful that transition risk is of primary importance for the two military hardware manufacturers. Also excluded are multinational conglomerates like General Electric, which has diverse divisions including aerospace, energy, healthcare, finance, and wind turbines (i.e., green technology). The three other firms tracked by Climate Action 100+ but not included in our list of heavy emitters are Procter & Gamble, Colgate-Palmolive, and Walmart. Notably, both Colgate-Palmolive and Walmart receive relatively favorable evaluations from Climate Action 100+ for their climate practices, indicating that they may be less exposed to transition risks. These firms may be included in the Climate Action 100+ list as future champions of green initiatives rather than obvious offenders.

3.2.4 LSE Transition Pathway Initiative (TPI) Centre firms

Similar to our comparison to the Climate Action 100+ firms, we verify if the firms tracked by the TPI Centre appear among those identified using our measure. The TPI Centre assesses the largest companies by market capitalization in the most emissions-intensive sectors, including electricity, aviation, and cement. TPI covers 99 firms in the CRSP sample, 84 of which we classify as heavy emitters. The TPI-covered firms come from 11 industries, which TPI assigns as follows: Airlines, Aluminum, Autos, Cement, Diversified Mining, Electricity Utilities, Food Producers, Oil & Gas, Paper, Shipping, and Steel. Notably, all firms in nine of the 11 industries are classified as heavy emitters. The Internet Appendix provides the

[36] A few firms tracked by Climate Action 100+, such as Shell and Suncor, are traded on NYSE, Amex, and Nasdaq, but their share codes (neither 10 nor 11) exclude them from the standard CRSP universe used for the Fama-French factors applied in this study. Only one US-headquartered firm, Bunge, a global agribusiness and food company incorporated in Switzerland, is removed from our sample due to our filters.

coverage details. Specifically, as noted in our earlier analysis, our basic approach does initially not classify automobile manufacturers as heavy emitters. We add internal combustion engine automobile manufacturers to our final list of heavy emitters and hence it includes Ford and GM that are tracked by the TPI Centre; however, we do not include Tesla and Rivian, which are the other two (electric) automobile manufacturers in their list of firms.[37] While four firms in the Steel industry are classified as heavy emitters, two smaller companies, Leggett & Platt and Reliance Steel & Aluminum, are not. Additionally, we classify six firms among the Food Producers as heavy emitters, but not the other eight, which include ConAgra Brands, General Mills, Hershey Company, J.M. Smucker, Kellogg, Kraft Heinz, McCormick & Co., and Mondelez. However, given their relatively low carbon intensity and diversified product offerings, it is arguable that these food companies are not severely exposed to transition risk, making their omission from the list of heavy emitters justifiable. In sum, this analysis again demonstrates that our method effectively identifies most of the firms vulnerable to carbon transition risks, aligning closely with the coverage provided by the TPI Centre.

3.2.5 Eversource Energy case study

Eversource Energy is a firm that has significantly reduced its carbon footprint but would not be classified as lowering emissions based on industry codes.

This publicly traded S&P 500 energy company operates New England's largest energy delivery system.[38] The company has transitioned much of its power generation from coal to natural gas, wind, hydroelectricity, and solar power. In 2016, Eversource launched a joint venture with Ørsted for the development of offshore wind farms. With the $1.6 billion merger with Aquarion Water Company two years later, the company expanded into the water supply sector. It sold its last five fossil fuel power plants in 2018. The following year, Eversource Energy announced an industry-leading goal to make its entire operations, including fleet, facilities and infrastructure, carbon neutral by 2030. Recently, Eversource has also begun installing over 400 electric vehicle charging stations in Massachusetts, converted its fleet to hybrid vehicles, and aimed to replace 40% of its diesel consumption with biofuel by 2023. To fund its transformation, Eversource Energy has issued 1.5 billion of green bonds since 2019.

[37] Cummins has recently been added to the TPI list and no assessment data is available in the historical Management Quality and Carbon Performance file for the period 2016-2023.

[38] As of 2023, the company serves approximately 4.4 million electric, natural gas and water utility customers in Connecticut, Massachusetts and New Hampshire. Before February 2, 2015, the company was known under the name Northeast Utilities.

However, during our sample period, the historical SIC (Standard Industrial Classification) code in Compustat is 4931, which is for Natural Gas Distribution, the GICS (Global Industry Classification Standard) code 551010 for Electric Utility, and the historical NAICS (North America Industrial Classification System) code is 2011, for Power Generation. In CRSP, the company's SIC code in 2015 and 2016 was 4911 (Electric Distribution), and thereafter it switches between 4911 and 4932 (Gas and Other Services Combined) several times until February 2021, before being assigned to SIC code 4924 (Natural Gas Distribution) thereafter. The NAICS code in CRSP is 221118 (Other Electric Power Generation) through January 2020 and 221210 (Natural Gas Distribution) for the remainder of the sample period. The SIC and NAICS codes therefore hardly identify the company's efforts to achieve its climate targets. In contrast, Trucost data shows that Eversource has reduced its Scope 1 carbon intensity by 94.7% over the period 2015–2023, and its Scope 2 and Scope 3 input intensities also decrease by 53.1% and 13.9% respectively.

This case demonstrates the robustness of our method in capturing a company's true carbon performance, highlighting the limitations of relying solely on industry classifications, which often fail to reflect dynamic changes.

3.2.6 Limitations of our classification approach

We use Scope 1 carbon intensity to identify heavy emitters and demonstrate in our robustness tests that considering the sum of Scope 1 and 2 emissions or the sum of Scope 1, 2, and upstream Scope 3 emissions does not materially change the categorization of heavy emitters. However, all the measures considered focus on the emissions intensity of the production process and do not account for the emissions from the final use of the product. This approach may overlook significant potential emitters, such as vehicle manufacturers. For example, manufacturers of electric cars and cars with internal combustion engines may be classified similarly. As a result, neither GM, Ford, nor Tesla make the top 10% of heavy emitters in any year of our sample. As we have mentioned earlier, Climate Action 100+ tracks GM and Ford, but not Tesla. As we discuss in the next subsection, private vehicles account for the majority of aggregate U.S. GHG emissions in the transport sector (a significant contributor), hence internal-combustion engine vehicle manufactures are important to consider. The same logic applies to heavy truck and machinery manufacturers like Caterpillar and Paccar, and the heavy-duty diesel and natural gas engine producer Cummins.[39] Hence, we add these

[39]On January 10, 2024, the U.S. Environmental Protection Agency (EPA) and the U.S. Department of Justice reached a $1.675 billion settlement agreement with Cummins for having installed devices designed

firms to our list of heavy emitters.

As previously noted, our categorization excludes aircraft manufacturers like Boeing. We confirm that including Boeing in our list of heavy emitters does not affect our results. However, given its involvement in military and space activities, it is unclear whether transition risk is the primary concern for the company. Moreover, commercial aircraft produced by Boeing are largely operated by publicly traded airline companies, and emissions from the use of these aircraft are recorded as Scope 1 emissions by the airlines. In fact, the total GHG emissions reported by airlines in our sample exceed the 130.7 million metric tons (Mmt) of CO_2e reported by the U.S. Environmental Protection Agency for the commercial aviation sector, as airlines disclose emissions from their global operations (EPA, 2024).

In contrast, for certain industries, such as oil and gas extraction, our approach of considering only Scope 1 emissions as a proxy for transition risk may be too conservative. Exxon reported direct Scope 1 emissions of 92 MmtCO_2e in 2023.[40] Of these emissions, 6.5% resulted from flaring and venting, a practice where oilfield operators burn or release the gas associated with oil production into the atmosphere rather than invest in the facilities and pipelines needed to capture it. Eliminating routine flaring and venting practices is technically feasible. For instance, Exxon has announced that they phased out routine flaring at their Permian Basin oil operations (in Texas and southwestern New Mexico) by the end of 2022. However, Exxon's self-reported Scope 3 emissions in 2023 from the sale of petroleum products amounted to 730 MmtCO_2e, which is roughly equivalent to Canada's total GHG emissions.[41] Therefore, in the case of Exxon, focusing only on direct Scope 1 emissions may significantly underestimate its transition risks.

3.3 Aggregate GHG emissions

In this subsection, we put the aggregate emissions of our sample into perspective by comparing them to the overall U.S. emissions. Aggregating only Scope 1 emissions to avoid double counting, our CRSP sample of publicly listed firms emitted approximately 2,050 million metric tons (Mmt) of CO_2e by the end of 2022.[42] According to the U.S. Environmental Protection Agency (EPA), total U.S. GHG emissions were 6,343.2 MmtCO_2e in 2022. Hence,

to bypass or disable emissions controls on 960,000 Dodge and Stellantis RAM pickup truck diesel engines between 2013 and 2023, plus $325 million in remedies and recalls (https://www.epa.gov/enforcement/2024-cummins-inc-vehicle-emission-control-violations-settlement).

[40] ExxonMobil (January 8, 2024), "2024 Advancing Climate Solutions: Executive Summary".

[41] See, Canada's official greenhouse gas inventory, https://www.canada.ca/en/environment-climate-change/services/climate-change/greenhouse-gas-emissions/inventory.html.

[42] The Internet Appendix plots aggregate emissions over time.

the firms in our sample represent around a third of total U.S. GHG emissions, an economically meaningful share. However, when we account for the large share of aggregate pollution produced by non-investable assets such as private vehicles, family-owned farms, and residential and government buildings, we find that our sample of firms represents nearly half of the aggregate annual U.S. GHG emissions stemming from investable assets. The details are discussed below. The largest share of aggregate U.S. emissions is from the transportation sector (28.4%), followed by the electricity power industry (24.9%), all other industries (22.9%), and agriculture (10.0%). Commercial and residential buildings account for 7.3% and 6.2% of total GHG emissions respectively (see Table 2-10 EPA, 2024).

With GHG emissions totaling 1,477 MmtCO_2e, road transport accounts for 81.5% of emissions within the transportation sector, while air transport accounts for 9.4%.[43] Road transport includes passenger cars, light-duty trucks, pickup trucks, sports utility vehicles, and minivans. The Bureau of Transportation Statistics estimates that private vehicles account for 58% of the total emissions in the transportation sector (Congressional Budget Office, 2022).[44] Thus, 16.5% of total U.S. GHG emissions ($0.58 \times 28.4\%$) come from private vehicles. The emissions from these vehicles are not accounted for as Scope 1 emissions by any other entity, and are not directly investable.

The agricultural sector accounts for 10% of total U.S. GHG emissions. According to the USDA America's Farms and Ranches annual report, 97% of U.S. farms are family-owned, contributing 90% of farm production (Whitt, Lacy, and Lim, 2023). Thus, at least 9.0% ($0.9 \times 10\%$) of aggregate U.S. emissions in this sector are not from investable assets. In fact, the agriculture sector in our sample of publicly-listed firms only covers 5.6% of the aggregate U.S. emissions from this sector. Similarly, residential real estate that accounts for 6.2% of total U.S. GHG emissions is essentially not investable through the stock market. Commercial real estate assets contribute 7.3% of total U.S. GHG emissions (Federal Reserve Board, 2024), however approximately 15% of commercial real estate in the U.S. is government-owned and, thus, non-investable (i.e., around 1.1% of aggregate emissions stems from the non-investable part of this sector).[45] Real estate investment trusts (REITs) cover less than 10% of the commercial real estate market (Nareit, 2021), and real-estate ETFs are small, primarily

[43]The remainder of the transportation sector emissions are from pipelines used for transporting liquids, gases, or slurries (3.8%), ships (2.8%), rail (2.0%), and lubricants (0.5%) (EPA, 2024).

[44]In 2022, light-duty trucks (660.2 MmtCO_2e) and passenger cars (369.5 MmtCO_2e) accounted for 69.7% of total road transport emissions. These vehicles are mostly private. Emissions from the use of medium- to heavy-duty trucks represented 28.0% of the road transport sub-sector (413.1 MmtCO_2e), while the remaining 2.3% came from buses and motorcycles (33.9 MmtCO_2e).

[45]Forbes (November 4, 2024), "Solving the mystery of government-owned real estate" by Julie Littman.

investing in REITs.[46] The asset pricing literature, however, typically excludes REITs and ETFs from the CRSP sample.

Taken together, around a third (32.8%) of aggregate U.S. pollution comes from non-investable assets, including private vehicles, agriculture, residential buildings, and government-owned commercial real estate.[47] Of the remaining 4,281.6 MmtCO_2e, our sample of U.S. CRSP firms covers 47.9%, an economically important share.

Public and private firms Although beyond the scope of this paper, it is interesting to consider the sources of other significant emitters not covered by our sample. We do not capture privately owned emitters, such as those in the oil sector. For example, Hilcorp is the largest privately held oil and gas company in the U.S., with a business model largely focused on acquiring existing oil and gas properties. The company produces 2.0 million barrels of oil equivalent per day (boe/d), second only to Exxon, which produces 2.4 million boe/d. The top 10 private oil firms produce 3.5 million barrels, and the top 100 about 7.5 million boe/d (Mou, 2021). Assuming that all firms in the oil sector have, on average, the same emissions per barrel of oil equivalent as Exxon, the top 100 privately owned oil firms account for approximately 337 million metric tons of CO_2e, or about 5.3% of total U.S. GHG emissions. Moreover, the contribution of private companies may increase in the future due to the practice of public companies selling their highly polluting assets to private firms, a practice known as brown-spinning (Gözlügöl and Ringe, 2022). Similarly, there are a few heavy emitters among state-owned utilities. For example, the federally owned Tennessee Valley Authority (TVA), which serves over 10 million people in Tennessee and parts of six neighboring states, ranks fourth among the highest absolute scope 1 GHG emitters.[48]

3.4 Heavy emitters descriptive statistics

Table 1 presents descriptive statistics (means and medians) for the set of heavy emitters, comparing them to the statistics for the other firms in the CRSP sample. On average, we identify 277 heavy emitters each year in our sample. Since heavy emitters are identified by sorting on carbon intensity, we observe a pronounced difference in carbon intensities between

[46]As of August 2024, there were 40 real estate ETFs with total market capitalization of only around $68 billion (https://etfdb.com/etfdb-category/real-estate).

[47]There are other sub-sectors we could add to this list. For example, emissions from the use of military aircraft (13.4 MmtCO_2e), which are 10% of the emissions from commercial aircraft, can be attributed to the U.S. Department of Defense.

[48]Trucost reports 41.1 MmtCO_2e emissions for TVA in 2023, accounting for around 0.6% of total U.S. GHG emissions.

heavy emitters and the remaining firms. The average carbon intensity of the top 10% most carbon-intensive firms is 6.180 metric tons (mt) of CO_2e per million US dollars in revenue, compared to only 0.164 mtCO_2e/US$M for the other 90% of firms. Notably, there are stark differences in absolute Scope 1 greenhouse gas emissions (total pollution) between these sets of firms as well, with the average emissions of the top 10% most carbon-intensive firms being 2.290 million metric tons (Mmt) of CO_2e, compared to only 0.065 MmtCO_2e for the other firms. This pattern is also evident when comparing the medians.

While the average firm size (measured by market capitalization) of heavy emitters is 27% larger, the median heavy emitter is more than twice as large as the median of the remaining firms. Heavy emitters are also more mature firms. The average firm age of these firms, measured as the numbers of years since the firm appears in CRSP, is 34 years compared to 21 years for the remaining firms. Similar to firm size, there is a stark difference in both the average and median Plant, Property, and Equipment (PPE) between heavy emitters and all other firms, with heavy emitters having, on average, around eight times more PPE (the difference in medians is even more pronounced). Moreover, we observe significant differences in book-to-market values, irrespective of whether we compare means or medians, with heavy emitters having a 36% higher mean book-to-market ratio than the remaining firms. The average dividend yield of heavy emitters is also significantly higher, and the median firm of the remaining 90% of firms does not pay dividends.[49] We observe lower levels of investment (scaled by total book assets) among heavy emitters, with their investment-to-asset ratio being 24% lower than that of other firms, but the median investment-to-asset ratio is identical. On the other hand, heavy emitters appear, on average, to be more profitable when examining operating profits (scaled by book equity), although the medians between these two sets of firms do not differ. The volatility of heavy emitters' stock returns is comparable to that of other firms' stocks, but their CAPM (market) betas are slightly higher. When sorting by size and book-to-market, potential differences in betas must be taken into account, as outlined in the discussion of our main results. Unsurprisingly, the raw (not industry-adjusted) standardized E scores from MSCI are lower for heavy emitters, though it is important to note that data coverage for E scores is about 20-30% lower than for the emissions data used in our analysis.

[49] On average, 67% of heavy emitters pay dividends, while only 49% of the remaining firms do.

4 Factor and anomaly portfolio composition

4.1 Fama-French factor portfolios

In this sub-section, we analyze the distribution of heavy emitters in Fama-French factor portfolios.

4.1.1 Fama-French portfolio construction

We follow Fama and French (1993), Fama and French (2015), and the methodology provided on Ken French's website to form Fama-French portfolios. These portfolios are constructed from all CRSP companies incorporated in the U.S. and listed on the NYSE, AMEX, or NASDAQ with CRSP share codes 10 or 11 (ordinary common equity). Firms are included only after they have appeared in Compustat for two years (Fama and French, 1993). The portfolios are rebalanced annually at the end of June. To be included, stocks must have positive book equity and market equity in December of the previous calendar year, and market equity must also be positive at the end of June. The median NYSE market value of equity at the end of June is used to split stocks into two size groups, Small and Big, based on the market value of equity (price times outstanding shares) (Fama and French, 1993). Stocks are also independently sorted at the end of June into three groups based on book-to-market equity for HML (High Minus Low) and SMB (Small Minus Big), operating profitability for RMW (Robust Minus Weak), and investment for CMA (Conservative Minus Aggressive), with breakpoints at the 30$^{\text{th}}$ and 70$^{\text{th}}$ percentiles. This double sorting results in six groups for each factor, with a varying number of stocks per group (see Lambert, Fays, and Hübner, 2020, for a discussion). The return of a value-weighted portfolio is calculated for each group. These portfolios are maintained for the next 12 months, and the proceeds from delisted companies are reinvested in the active portfolio. The first monthly return after rebalancing is at the end of July, with the final return in June of the following year.

The long position of the SMB factor is the equally weighted average of the three small-cap portfolios with high, neutral, and low book-to-market ratios; the short position is the equally weighted average of the three large-cap portfolios. HML is the equally weighted return of the two value portfolios (Small Value and Big Value) minus the equally weighted return of the two growth portfolios (Small Value and Big Value), RMW is the equally weighted return of the two portfolios with robust operating profitability minus the equally weighted return of the two portfolios with weak operating profitability, and CMA is the equally weighted return of the two conservative investment portfolios minus the equally weighted return of the two aggressive investment portfolios. The large neutral and small neutral portfolios are excluded when calculating the long and short positions for the HML, RMW, and CMA factors.

4.1.2 Heavy emitters in Fama-French portfolios

We assess the prevalence of heavy emitters in Fama-French characteristic-sorted portfolios by evaluating the proportion of heavy emitters in each portfolio. Our primary focus is assessing whether there is a significant difference in the proportion of heavy emitters between the long leg (e.g., Value) and the short leg (e.g., Growth) of a given strategy. At the same time, we also want to assess whether heavy emitters represent a disproportionate share of any one specific portfolio. Table 2 presents the market capitalization share of heavy emitters in Fama-French characteristic-sorted portfolios.

Size We begin with the two portfolios sorted on size, presented in Panel A of Table 2. Recall that heavy emitters by construction represent 10% of the available firms in each year, which, as reported earlier, amounts, on average, to 12.3% of the total market capitalization. Consequently, if heavy emitters are evenly represented across the characteristic-sorted portfolios, we would expect them to account for around 12.3% of each portfolio's value on average. Hence, we test whether the fractions of heavy emitters are statistically significantly different from the unconditional sample mean share, denoted as $\bar{w}_v$ for market capitalization and $\bar{w}_n$ for the number of firms. Since these portfolios are value-weighted in practice, we focus on the value weights as the more economically relevant quantity, and present the firm count shares in the Internet Appendix. As we have already seen in Table 1, heavy emitters tend, on average, to be larger firms. Heavy emitters represent, on average, 13% of the Big portfolio (t-stat $= 1.14$ for the test of whether the mean is different from $\bar{w}_v$), and 8% of the Small portfolio (t-stat $= -8.05$). The difference between the two is highly statistically significant. In summary, we find that investors in small-cap stocks tend to have relatively lower exposure to heavy emitters compared to those who focus on larger stocks.

Value In Panel B we examine the book-to-market-sorted portfolios. Notably, these are double sorts: stocks are first sorted by size and then by book-to-market. Hence, the relevant null share is the conditional share of heavy emitters among Big and Small stocks (i.e., the shares reported in Panel A above). We denote the conditional means as $\bar{w}_v^k$, with $k =$ Small or Big. A clear pattern emerges: heavy emitters disproportionately dominate Value portfolios and are significantly underrepresented in Growth portfolios. On average, heavy emitters represent 37% of the Big Value portfolio (t-stat = 10.97 for the test of whether the mean differs from $\bar{w}_v^{\text{Big}}$), but only 3% of the Big Growth portfolio (t-stat = −34.78 for the same test). The difference, 34%, is also highly statistically significant (t-stat = 15.00). Notably, the shares of heavy emitters in these portfolios remain stable over time throughout our main sample period. A similar pattern is observed among the Small Value and Growth portfolios, though the proportion of heavy emitters is lower in the Small Value portfolio, at 14% (t-stat = 10.02 for the test of whether the mean differs from $\bar{w}_v^{\text{Small}}$), and only 4% in the small Growth portfolio (t-stat = −9.97 for the same test), with the difference, 10%, being statistically significant (t-stat = 15.62).[50] Looking at the share in terms of the number of firms, we observe similar results (reported in the Internet Appendix).

Using the Fama-French method and combining these portfolios to form the HML factor, we find that HML has an average net long position in heavy emitters of approximately 22%, representing a statistically and economically significant exposure. This result aligns with the findings of Pástor et al. (2022), who demonstrate that a regression of their brown-minus-green portfolio returns exhibits a negative loading on the HML factor.

Lastly, to ensure that the observed patterns are not driven solely by the recent sample period, we repeat the analysis using the extended sample (2005–2023), which incorporates backfilled emissions data when none is available to identify heavy emitters. While the disproportionate exposure of Value portfolios to heavy emitters is slightly attenuated in the longer sample (for instance, the big Value portfolio holds 34% in heavy emitters on average), all the observed patterns remain consistent.

Taken together, our findings show that Value portfolios are systematically overexposed to heavy emitters, aligning with the common intuition that Value stocks are often found in capital-intensive industries. However, our results highlight that these stocks are not only capital-intensive but also disproportionately composed of the most polluting firms, and in particular in Value portfolios of large-cap stocks.

Investment Turning to investment-sorted portfolios (Panel C), we do not observe pronounced differences between the long leg (Conservative investment) and the short leg (Aggressive investment) of the strategy. While heavy emitters appear slightly more prevalent in the Big Conservative portfolio than in the Big Aggressive portfolio, the differences are small

[50]Notably, our emissions data covers, on average, 97% of the Big Value portfolio (with similar coverage for the Big Growth portfolio), but only 62% of the Small Value portfolio (untabulated). This means that we can classify almost all large firms as heavy or light emitters, but only about 60% of small firms. Firms without emissions data are retained in the sample and classified as light emitters, so the proportion of light emitters in the Small Value portfolio is a lower bound, as some unclassified firms may actually be high emitters.

and unstable. On average, heavy emitters represent 13% of the Big Conservative portfolio (essentially identical to the conditional mean) and 8% of the Big Aggressive portfolio (t-stat $= -4.73$ for the test of whether the mean differs from $\bar{w}_v^{\text{Big}}$), with the 5% difference being statistically significant (t-stat $= 2.22$). However, in the longer sample, the difference shrinks to only 2%, and the statistical significance disappears. Looking at the share in terms of the number of firms, we observe similar results, with the only difference being that the gap remains statistically significant in the longer sample, though still very small (reported in the Internet Appendix). The shares of heavy emitters in the Small Conservative and Small Aggressive portfolios do not appear to differ discernibly.

These patterns can be partly explained by the fact that investments among heavy emitters are highly cyclical, as these firms predominantly come from energy and other commodity-producing industries, such as mining. This is illustrated in Figure 7(a), which plots the time series of aggregated investment for heavy emitters and light emitters (light emitters are stocks not classified as heavy emitters) relative to the Goldman Sachs Commodity Index (GSCI). Between 2005 and 2023, the correlation between the investment of heavy emitters and GSCI is 0.35. In contrast, the correlation between the investment of light emitters and GSCI is -0.21. During our main sample period these correlations are 0.70 and -0.25, respectively. Visually, the positive relationship is particularly evident in 2015, when we see a collapse in investment among heavy emitters coinciding with the oil price crash between 2014 and 2016.[51] Similarly, robust investment is observed among heavy emitters in 2022 at the time of increasing commodity prices, while investment by light emitters is dramatically reduced. The strong cyclicality of heavy emitters leads to relatively high turnover in investment-sorted portfolios. For instance, heavy emitters made up a large share of the Big Conservative portfolio in 2017 (22%) following poor commodity market performance, but only 5% in 2023 after strong commodity market performance.

Profitability In Panel D, we examine the operating-profitability-sorted portfolios. We observe more nuanced patterns. Specifically, heavy emitters are significantly under-represented in the Big Robust profitability portfolio, with only a 7% share (t-stat $= -12.12$ for the test of whether the mean differs from $\bar{w}_v^{\text{Big}}$). Heavy emitters are also over-represented in the Big Weak profitability portfolio, with an average share of 29% (t-stat $= 2.88$ for the test of whether the mean differs from $\bar{w}_v^{\text{Big}}$). The -22% difference is statistically significant (t-stat $= -3.99$). However, this pattern is much less pronounced when examining the share in terms

[51]The oil price collapse between 2014 and 2016 is primarily attributed to a supply glut caused by the boom in U.S. shale oil production (Stocker, Baffes, Some, Vorisek, and Wheeler, 2018).

of the number of firms, with the difference in shares of heavy emitters between Robust and Weak portfolios being in the same direction but not statistically significant from zero in our main sample.

In contrast, among Small stocks, heavy emitters tend to be over-represented in the Small Robust portfolio, with an average share of 13% (t-stat = 2.47 for the test of whether the mean differs from $\bar{w}_v^{\text{Small}}$), and slightly under-represented in the Small Weak portfolio, with an average share of 7% (not statistically different from $\bar{w}_v^{\text{Small}}$). Although this 6% difference is statistically significant, it is economically small (the difference further decreases to only 3% in the extended sample period but remains statistically significant).

In sum, our results suggest that large heavy emitters are typically less profitable and are less likely to appear in the long leg of profitability-sorted portfolios, indicating that profitability sorting large firms may inadvertently minimize transition risk or even hedge it if investors could short. However, sorting small stocks by profitability may have the opposite effect on portfolio composition.

Momentum Lastly, as a placebo test, we also examine momentum-sorted portfolios. Given the high turnover of momentum portfolios, we expect heavy emitters to be equally likely to be assigned to any of the momentum portfolios ex ante. In line with expectations, our analysis reveals no meaningful differences in the concentration of heavy emitters between momentum winner and loser portfolios, highlighting their significant presence in other portfolios, particularly Big Value.

4.2 Anomaly portfolios

We also analyze 161 anomaly portfolios from Chen and Zimmermann (2021) with adequate coverage in our U.S. sample. Our focus is on anomaly portfolios related to value/growth, investment, and profitability themes to support our main findings from the Fama-French portfolios. We group the anomaly strategies into these themes based on prior literature and report notable patterns, including high proportions of heavy emitters in other characteristic-sorted portfolios, in the Internet Appendix.

Table 3 presents the results. Starting with the value-type strategies in Panel A, we observe a clear and consistent trend: heavy emitters are more commonly found in the long leg (value) portfolios. Specifically, for the portfolios sorted on intangible return from Daniel and Titman (2006), heavy emitters are more prevalent in portfolios with low intangible returns (the proportion in portfolio 5 is 37%). The proportion of heavy emitters in portfolio 1, which has high intangible returns, is comparable to that of Big Growth. A similar pattern is observed for cash productivity-sorted portfolios from Chandrashekar and Rao (2009), with heavy emitters concentrated in portfolios 4 and 5, which have low cash flow productivity. The differences between the long and short legs, shown in the last column, are significant for both the main sample period 2016-2023 and the extended sample period 2005-2023. For the decile portfolios of enterprise multiples from Loughran and Wellman (2011), the proportions of heavy emitters are higher in portfolios 4-10 and significantly lower in the three decile portfolios with the highest enterprise multiples. The proportions of heavy emitters in portfolios sorted on operating cash flow to price from Desai, Rajgopal, and Venkatachalam (2004), long-term EPS forecasts from La Porta (1996), and employment growth from Belo, Lin, and Bazdresch (2014) confirm the pattern: heavy emitters are more prevalent in portfolios with higher operating cash flow to price, higher cash flow to market value, higher sales to price, lower EPS forecasts, and lower employment growth – characteristics typically associated with value firms. Furthermore, value stocks tend to have shorter equity duration and higher dividend yields compared to growth stocks, and we find that the proportion of heavy emitters is larger in low implied equity duration (Dechow, Sloan, and Soliman, 2004) and high predicted dividend yield (Litzenberger and Ramaswamy, 1979a) portfolios. A substantial fraction of tangible assets is often associated with high carbon intensity or low E scores (e.g., Gibson Brandon, Krueger, and Schmidt, 2021), such as firms in the Energy sector.[52] However, nearly half of the firms in portfolio 5, sorted on tangibility from Hahn and Lee (2009) during the period 2016-2023, are from the Health sector, which is characterized by high tangible assets and low emissions. Firms that we classify as heavy emitters, such as Energy firms, instead dominate portfolio 4 during this period. In sum, regardless of how value is defined or how the strategy is constructed, we observe a consistent pattern: heavy emitters are significantly more prevalent among value stocks and considerably less prevalent among growth stocks.

Next, we examine alternative investment-sorted portfolios in Panel B of Table 3. Specifically, we consider asset growth from Cooper, Gulen, and Schill (2008); change in capex from Anderson and Garcia-Feijoo (2006); and investment to revenue from Titman, Wei, and Xie (2004). In all cases, we observe a pattern similar to our analysis of Fama-French portfolios: heavy emitters are less prominent in aggressive investment portfolios and slightly more prominent in conservative investment portfolios. However, these patterns appear to be unstable over time.

[52]In Section 3.2.2, we discuss the inverse relationship between high carbon intensity and low E scores.

We also consider alternative profitability-sorted portfolios (Panel B of Table 3). Novy-Marx (2013) uses gross profitability (calculated as sales minus the cost of goods sold, scaled by total assets), while Fama and French (2015) use operating profitability (sales minus cost of goods sold and selling, general, and administrative expenses, scaled by book equity) to construct RMW portfolios. During both the 2016–2023 period and the extended sample period beginning in 2005, the bottom quintile portfolios 1 and 2, which consist of low-profitability companies, exhibit a share of about 40% heavy emitters. In contrast, the high-profitability portfolios 4 and 5 have a significantly lower proportion of heavy emitters. The differences between the short and long legs appear more pronounced than those observed for the RMW factor in Table 2.[53] Similarly, when applying the Lev and Nissim (2004) method for sorting stocks by taxable income, heavy emitters are concentrated in the lowest taxable income portfolio. Sorting stocks into deciles based on R&D-adjusted operating profitability as in Ball, Gerakos, Linnainmaa, and Nikolaev (2016) further corroborates the finding that low-operating profitability portfolios – specifically deciles 1-3 – contain the highest proportions of heavy emitters. These results reinforce the conclusion that low-profitability portfolios have substantially higher proportions of heavy emitters, consistent with the RMW findings.

The Internet Appendix presents the results for the anomalies in Chen and Zimmermann (2021) that are indirectly related to the Fama-French (2015) characteristics of value, investment, and profitability, such as the cash-to-asset ratio, as well as those that capture other dimensions like EPS forecast dispersion, pension funding status, or organizational capital. Consistent with our methodology, we include only those anomalies for which we have adequate emissions data coverage. Additionally, we limit ourselves to reporting only the findings for anomalies where distinct patterns in the proportions of heavy emitters are evident across the decile or quintile portfolios during our main and extended sample periods.

The 48% share of heavy emitters in the lowest cash-to-asset decile 1 is in stark contrast to the portfolios 8-10 with a high cash-to-asset ratio, which are only marginally or not at all invested in shares of heavy emitters (the difference of -47% between deciles 10 and 1 is highly significant with a t-stat of 19.18). The presence of heavy emitters gradually declines with higher cash-to-asset ratios. Thus, heavy emitters are concentrated in the short leg of the cash-to-asset anomaly analyzed by Palazzo (2012). Similarly, heavy emitters are overrepresented in the portfolios characterized by low earnings consistency (Alwathainani, 2009), high cash-flow to price variance (Haugen and Baker, 1996), or high EPS forecast dispersion (Diether, Malloy, and Scherbina, 2002). Again, for all three characteristics, heavy

[53] We conjecture that the same tilts will also carry over to the R&D-adjusted profitability factor of Jagannathan, Korajczyk, and Wang (2023).

emitters are overrepresented in the short leg (portfolio 1) of a long-short strategy to exploit the anomaly. Heavy emitters are also overrepresented in portfolios with other undesirable characteristics such as low pension plan status (Franzoni and Marin, 2006), and low organizational capital (Eisfeldt and Papanikolaou, 2013). Finally, a higher net debt-to-price ratio indicates higher financial leverage and higher stock price volatility due to the magnifying effect of debt on returns (Penman, 2007). Heavy emitters represent, on average, 46% of the firms in the highest net debt-to-price portfolio (quintile 1) for the 2016-2023 period (and 45% over the extended sample period), however, what stands out is portfolio 5 comprised of firms with low net debt-to-price ratios: only 2% of this quintile's market capitalization is allocated to stocks of heavy emitters. The differences between quintiles 5 and 1 are highly statistically significant (t-stats of -26.11 and -13.44, respectively).

In sum, heavy emitters are concentrated in portfolios with undesirable traits such as low cash-to-assets ratios, high net debt, inconsistent earnings, high cash flow variance, low pension funding status, and low organizational capital. Heavy emitters are prevalent in the short leg of strategies to exploit anomalies regarding these characteristics. Our findings highlight the significant presence of heavy emitters in various factor and anomaly portfolios, emphasizing the importance to identify potential transition risks investors may face (or avoid) when following these well-known investment strategies.

5 Returns

In this section, we first investigate whether investors receive or expect to receive compensation for their exposure to transition risk when holding heavy emitters. We conduct this analysis by examining the Fama-French Big Value portfolio, dividing it into segments of heavy and light emitters (where light emitters are defined as firms not classified as heavy emitters) and comparing their realized and expected returns estimated using the ICC approach. Focusing on the value portfolios is natural, given their importance in the literature and in practice. Importantly, we focus on the Big Value portfolio because heavy emitters represent, on average, close to 40% of market capitalization, allowing us to compare two portfolios of similar importance.[54] In other words, we compare two portfolios with similar

[54]In contrast, heavy emitters represent, on average, only around 12% of the Small Value portfolio. Moreover, as shown in the Internet Appendix, the coverage of small firms in the ICC data is limited, making inference difficult. Nevertheless, we repeat the analysis on the Small Value portfolio and find qualitatively similar results.

fundamental characteristics, but different carbon emissions.[55]

Second, we compare the realized and expected returns of the light emitters in Big Value with those in Big Growth to contribute to an active debate in the literature on whether the outperformance of growth relative to value strategies in the recent decade was significantly driven by investors' green preferences and carbon transition risk considerations (see, e.g., Pástor et al., 2022). We focus on light emitters as they constitute the bulk of both the Value and Growth portfolios, allowing us once again to compare two broad portfolios.[56] Specifically, this analysis controls for firms' carbon emissions, comparing two portfolios with similar emissions, but different fundamental characteristics.

For this analysis, we exclude firms from the utility sector due to their distinct return behavior and low market betas, with government oversight influencing their pricing, profitability, and investment decisions. Notably, our Big Value heavy emitter and low emitter portfolios align on key characteristics such as size and book-to-market ratios, and in our sample, they show comparable market betas. The market beta for Big Value heavy emitters and light emitters is 1.30 and 1.25, respectively, and the difference is not statistically distinguishable from zero.

5.1 Carbon intensity, absolute pollution, and E scores comparison

In this sub-section, we show that light emitters in the Big Value portfolio are as 'green' as the light emitters in the Big Growth portfolio. Before drawing this conclusion, Table 4 first compares the value-weighted carbon intensity of heavy and light emitters in Big Value. By construction, the average Scope 1 carbon intensity of heavy emitters is higher than that of light emitters, but the difference is striking. In fact, the carbon intensity of heavy emitters (3.876 mtCO_2e per million $ in revenue) is almost 50 times larger than that of light emitters and statistically highly significant (t-stat = 6.94). The differences in carbon intensities remain significantly higher if we include Scope 2 and Scope 3 emissions in the definition of carbon intensity. The difference in absolute Scope 1 emissions is even more pronounced (emissions are 113 times larger for heavy emitters compared to light emitters),[57] and E scores are substantially lower (worse) for heavy emitters compared to light emitters.

[55] The methodology of comparing firms with otherwise similar characteristics is in the spirit of D'Amico, Klausmann, and Pancost (2023), and Larcker and Watts (2020), who specifically study German 'twin' government bonds and municipal bonds, respectively.

[56] Recall that heavy emitters represent only around 5% of the Big Growth portfolio.

[57] Bolton and Kacperczyk (2021) argue that environmental regulation is more likely to target firms with high levels of pollution, and renewable energy tends to displace fossil fuels in firms where economies of scale are highest.

In the last column of Table 4, we compare emissions and E scores of light emitters in Big Value and Big Growth. The key findings from this comparison are that (1) the differences in carbon intensities between light emitters in the Big Value and Big Growth portfolios are economically small compared to the substantial differences between heavy and light emitters in Big Value, and (2) the differences in carbon intensities between light emitters in the Big Value portfolio are not statistically significant compared to those in the Big Growth portfolio for the main sample period 2016-2023, and are actually smaller in the extended sample period 2005-2023 (t-stat $= -4.04$). This result also holds when total Scope 1 plus Scope 2 emissions during the 2016-2023 period are considered to compute carbon intensity. For the extended sample period 2005-2023, and when carbon intensity further includes upstream Scope 3 emissions, light emitters in Big Value are even less polluting than light emitters in Big Growth. The difference is statistically significant, although the environmental impact of the difference may be debatable (t-stat $= -3.98$). We draw the same conclusion that the light emitters in Big Value are not less 'green', on average, than the light emitters in Big Growth when comparing total pollution (without scaling by revenue) or E scores instead of carbon intensity. Total absolute Scope 1 emissions are significantly higher, and (standardized) E scores significantly lower (i.e., worse), for light emitters in Big Growth compared to light emitters in Big Value over both the 2016-2023 period and the extended sample period 2005-2023.[58] In conclusion, on all GHG emission metrics and E scores, the light emitters in the Big Value portfolio are, on average, as 'green' as the light emitters in Big Growth.

5.2 Realized returns

Figure 8(a) plots the cumulative value-weighted returns of the two sub-portfolios that comprise the Big Value portfolio: Big Value heavy emitters (solid brown line) and Big Value light emitters (solid green line). The realized returns of the two sub-portfolios are then compared to the Big Growth portfolio (dashed blue line).

First, we compare the heavy and light emitters in Big Value. Although the realized returns of these two portfolios show prolonged periods where heavy emitters outperformed light emitters, the cumulative returns of the two sub-portfolios were almost identical from the beginning of the sample period in 2005 until the Paris Agreement, and again from that point until the onset of the COVID crisis. During the remainder of the sample period, the

[58] All signs of the difference tests remain the same when equal-weighted portfolios are used instead of value-weighted portfolios. However, the differences become insignificant for the E scores in the main sample 2016-2023 and for the absolute Scope 1 emissions in the extended sample 2005-2023. The results are presented in the Internet Appendix.

heavy emitters in the value portfolio once again exhibit higher cumulative returns. We also observe the well-documented strong performance of the Big Growth portfolio in recent years (see, e.g., Israel, Laursen, and Richardson, 2020). Equal-weighted portfolios (plotted in the Internet Appendix) exhibit similar patterns.

In Panel A of Table 5, we provide a formal test of the observed return differences between heavy and light emitters in the Big Value portfolio, as well as the return differences between light emitters in the Big Value portfolio and the Big Growth portfolio over our extended sample period (Table 5 also presents ICC results, which we discuss in the next section). Specifically, we estimate a time series ordinary least squares regression of the return spread on time period dummies: dummy variables for the period after the Paris Agreement in December 2015 (Post Paris), and the high inflation period 2021/2022 (Post 2021).

As we observe in column (1), unconditionally the average annualized value-weighted return of heavy emitters relative to light emitters of the Big Value portfolio was 4.26% higher. However, this positive average difference is not statistically significant and, in line with visual analysis, appears to be primarily driven by the 2021-2022 high inflation period, when the annualized performance of the high-emitting Big Value portfolio was 40.39% and highly statistically significant. In contrast, the period between 2015 and 2021 is associated with an underperformance of the heavy emitters of around 3.27% on an annualized basis, although this difference is not statistically significant. Excluding the 2021-2022 period, the average difference between high and light emitters of Big Value is reduced to only around 0.11% per annum (not tabulated). The equal-weighted portfolios (shown in the Internet Appendix) exhibs similar patterns.

To further explore the potential drivers of this spread between heavy and light emitters, we examine aggregate commodity prices over time. In Figure 8(b), the cumulative return spread between heavy emitters and light emitters in the Big Value portfolio is plotted against the cumulative returns of the GSCI return index, which serves as a benchmark for investments in commodity markets. The correlation between monthly returns of the GSCI index and the Big Value heavy minus light emitters spread is 44% over the sample period 2005-2023, while the correlation between the plotted cumulative return indices is 71%, highlighting that fluctuations in commodity prices are a key driver of the temporary divergence in cumulative returns between heavy and light emitters within the Big Value portfolio. For example, the commodity price boom during the inflationary period of 2021-2022, which was further exacerbated by the onset of the war in Ukraine, is associated with strong outperformance of the heavy emitters. The opposite occurred during the lockdowns of the pandemic in early

2020, when the heavy emitters appeared to underperform.[59] These patterns align with the study of Shi and Zhang (2024), who find that oil price changes help explain fluctuations in the 'greenium.' However, given that heavy emitters are not exclusively oil-producing firms, we find that the GSCI has a higher explanatory power for the spread between heavy and light emitters.[60]

Given the notable variation in performance between high and light emitters in the Big Value portfolio over the short run, inferences based on realized returns may be sample-dependent. Nevertheless, our analysis suggests that the realized returns of heavy and light emitters in Big Value are similar over the long run. Temporary deviations occur, but appear to be driven by commodity cycles, rather than persistent differences in expected returns.

Second, we examine the realized return differences between Big Value light emitters and Big Growth light emitters. In column (4) of Panel A in Table 5, we observe that, during our sample period, the average annualized value-weighted return of Big Value light emitters relative to Big Growth light emitters was 3.35% lower (not statistically significant). In particular, this difference is driven predominantly by the period between 2015 and 2021, during which light emitters of the Big Growth portfolio outperformed the light emitters of the Big Value portfolio by 10.20% per year, on average (statistically significant at the 10% level and economically large). Both portfolios are comprised exclusively of light emitters, and Big Value light emitters and Big Growth light emitters are, on average, equally 'green'. Hence, any differences in their performance cannot be attributed to shifts in green preferences or shocks to brown firms.

We also examine the risk-adjusted returns of the different portfolios. We use exposures to Fama-French systematic risk factors, MKT, SMB, CMA, and RMW for risk adjustment, omitting HML since we are working with the Value and Growth portfolios used in its construction. We find that the risk-adjusted return difference between heavy-emitter and light-emitter Big Value portfolios is economically and statistically insignificant.In contrast, the risk-adjusted returns of light Big Value (and heavy Big Value) portfolios relative to the light Growth portfolio are negative, statistically significant, and economically large. Table 6 summarizes the results. In column (1), we repeat the average annualized value-weighted return difference of 4.26% between Big Value heavy and light emitters over our sample period. As mentioned earlier, the market betas for these two portfolios are not statistically significantly

[59] This result is in line with Bansal, Wu, and Yaron (2022) who show that socially responsible investments underperform in recessions.

[60] The correlation between monthly changes in oil prices and the Big Value heavy minus light emitters spread is only 17% during our sample period.

different, so the MKT factor in column (2) cannot explain the observed return differences. When we add the other factors from the Fama-French 5-factor model (excluding HML), the unexplained return difference is reduced to 1.03%, which is not statistically significant. In columns (4)-(6), we compare Big Value light emitters and Big Growth light emitters. Since Big Value light emitters have, on average, higher market betas in our sample, the risk-adjusted return difference in column (5) increases to −6.29% and becomes statistically significant (t-stat = −2.32). Controlling for the other Fama-French factors in column (6), we find that the risk-adjusted return difference decreases slightly to −5.18%, but remains statistically significant (t-stat = −2.42), confirming the puzzling documented outperformance of Growth stocks over Value stocks during our sample period. As previously noted, the light-emitter Big Value and light-emitter Big Growth portfolios are equally 'green'; thus, the difference in risk-adjusted returns cannot be primarily attributed to their environmental characteristics.

5.3 Expected returns using ICC estimates

Due to the relatively short history of pollution data, E scores, and other transition risk proxies, inferences about expected returns based solely on realized returns are limited. We therefore turn to the implied cost of capital to analyze investors' return expectations.

5.3.1 ICC construction

We follow Mohanram and Gode (2013), Lee, So, and Wang (2021), and Eskildsen et al. (2024) and use for each firm the equal-weighted average of four ICC measures: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). Since the focus of our analysis is on heavy and light emitters within the Fama-French Big Value and Big Growth portfolios, the coverage for these ICC measures based on analyst forecasts over the extended sample period 2005-2023 exceeds 95% of market capitalization for all four portfolios Big Value heavy emitters, Big Value light emitters, Big Growth heavy emitters, and Big Growth light emitters.[61]

The ICC is the internal rate of return that equates the current stock price with the present value of its expected future cash flows. Gebhardt et al. (2001) apply a residual income valuation model based on Ohlson (1995), where the value of a stock is the sum of the book value of equity and the present value of expected future residual income, defined as the

[61]The average coverage across the four portfolios is 97.8% (the Internet Appendix shows the coverage).

difference between the firm's earnings, estimated from analysts' forecasts, and a charge for the cost of capital on its book value. They use mean analysts' EPS forecasts from I/B/E/S for the first two years and the expected dividends payout (from historical data) do derive book value and return on equity (ROE) forecasts. Firms' ROE converges thereafter to the median industry ROE. We use data from Eskildsen et al. (2024), who set a ten-year horizon for the gradual adjustment toward the industry ROE and calculate the industry target ROE using a ten-year moving window of the median past ROEs of all firms within the same Fama-French 49 industry.[62] Finally, a terminal value is added, with the residual income forecast 12 years into the future used to estimate residual income in perpetuity. Claus and Thomas (2001) assume a similar specification of a residual income model where analysts' consensus long-term growth rates are used until year five and earnings grow at the rate of inflation (set equal to the yield on 1-year Treasury minus 3%) thereafter. In the Ohlson and Juettner-Nauroth (2005) abnormal earnings-growth valuation model, earnings growth declines asymptotically to the long-run growth rate of the economy. Finally, Easton (2004) is a simplified version of the Ohlson and Juettner-Nauroth (2005) model without dividends, where the price/earnings-to-growth (PEG) is used, incorporating expected earnings growth into the price-earnings earnings ratio.

5.3.2 ICC results

Figure 9 compares the value-weighted ICCs for heavy emitters (solid brown line) and light emitters (solid green line) within the Big Value portfolio, as well as those for Big Growth (dashed blue line). The plot shows that the ICCs of the heavy and light emitters of the Big Value portfolio were very similar until the beginning of 2017, when the difference became positive until the onset of the COVID crisis in 2020, after which they reverted to being similar.[63] Columns (1)-(6) of Panel B in Table 5 confirm the visual intuition: unconditionally, the average difference between the ICCs of high and low emitters in the Big Value portfolio is around zero. However, in the period from 2015 to 2020, the difference was, on average, positive and 1.13% per year (statistically significant at the 10% level with t-stat = 1.85).[64]

[62]This involves a linear interpolation between the second-year analysts' consensus earnings forecast divided by the book value after one year and the median industry ROE. In their original specification Gebhardt et al. (2001) also use the long-term growth rate to impute a three-year-ahead earnings forecast, before ROEs revert to the industry median. Additionally, they compute the industry ROE over a shorter five-year window.

[63]Seltzer, Starks, and Zhu (2022) also find that credit ratings for corporate bonds from high-carbon issuers have deteriorated following the Paris Agreement.

[64]Using equal-weighted averages of the ICCs of the stocks within each portfolio (reported in the Internet Appendix) corroborates the patterns of the value-weighted portfolio, with one notable difference being that

This increase in the ICC of the heavy emitters in the Big Value portfolio coincided with the increased demand for ESG investments as shown by Gormsen and Huber (2024). Additionally, this time period also saw elevated levels of climate risk concerns among investors, as inferred from earnings calls transcripts (Sautner, Van Lent, Vilkov, and Zhang, 2023a). Among the often conflicting empirical studies on transition risk premiums, our results are consistent with Sautner et al. (2023b), who, studying option-implied expected return proxies, find an economically small and fluctuating premium associated with their measure of climate change exposure.

Taken together, the results strongly suggest that there is no persistent, significant difference in the ICCs of heavy and light emitters in the Big Value portfolio. In other words, apart from the temporary divergence between 2017 and 2020, investors typically do not demand a higher expected return from heavy emitters of the Big Value portfolio compared to the low emitters in the same portfolio.[65]

In stark contrast, there is a highly persistent and significant difference between Big Value light emitters and Big Growth light emitters. As shown in column (4) of Panel B in Table 5, over the full sample period, the average value-weighted ICC of Big Value light emitters was 2.87% higher (statistically significant, t-stat = 9.30). Notably, the difference significantly increased in the post-2015 period, with the change stemming from the decrease in the ICCs of the Big Growth light emitters, as observed in Figure 9. We emphasize that both portfolios are comprised of low emitters. Moreover, the results for the value-weighted and equal-weighted portfolios (reported in the Internet Appendix) are very similar. Hence, although low emitter Growth portfolios may contain a few unique 'green champions' like Tesla, it is highly unlikely that either the large persistent difference in average ICCs or the recent increase in that difference between low emitter Value and low emitter Growth portfolios is driven by green preference shifts to any meaningful degree.

6 Conclusion

Addressing transition risk is crucial for investors, particularly when assessing exposure to the heaviest emitters, which are arguably most vulnerable to the uncertainty surrounding the carbon transition. Using firm-level emissions data, we show that just 10% of the most

the equal-weighted heavy emitter Big Value portfolio ICC displays a spike at the time of the Paris Agreement.

[65] In the absence of a compensation for bearing transition risk, hedging these risks becomes even more important (see, e.g., Andersson, Bolton, and Samama, 2016; Engle, Giglio, Kelly, Lee, and Stroebel, 2020; Cepni, Demirer, and Rognone, 2022; De Nard, Engle, and Kelly, 2024).

carbon-intensive firms (heavy emitters) account for over 90% of all Scope 1 emissions from publicly listed U.S. companies. This concentration of emissions highlights the importance of understanding how these firms are represented in investment portfolios.

Our analysis reveals that heavy emitters are disproportionately represented in key factor portfolios, particularly in value-oriented strategies such as the Fama-French Big Value portfolio, where around 35% of the portfolio's market capitalization is typically made up of heavy emitters. In contrast, heavy emitters are significantly underrepresented in Growth portfolios. The persistence of these patterns across different factor portfolio strategies underscores the transition risks that investors may unknowingly bear.

We find that even within the Big Value portfolio, there is a large dispersion in emissions across firms, and the Big Value light-emitter portfolio is as green as the Big Growth light-emitter portfolio. Even though the Big Value light-emitter portfolio's emissions are significantly lower than those of the Big Value heavy-emitter portfolio, we find that they both have about the same average realized returns, realized risk-adjusted returns, as well as expected returns (measured by the ICC). These findings suggest that the market currently provides little incremental compensation for bearing transition risk. In contrast, the expected return of Big Value light-emitter portfolio is significantly higher than that of Big Growth light-emitter portfolio (with the difference significantly increasing in recent years), despite no meaningful differences in their carbon intensity, absolute pollution, or E scores (i.e., their 'greenness').

Our findings highlight the importance for investors to understand the carbon exposure inherent in their strategies to effectively manage potential transition risks. Moreover, our results suggest that the superior performance of growth stocks relative to value stocks in recent years is not necessarily driven by growth stocks being predominantly green or by a sharp rise in investors' preference for green firms.

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Table 1: Descriptive statistics

This table presents summary statistics for the heavy emitters and remaining firms in the CRSP sample. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the five least carbon intensive firms substituted for the five firms producing vehicles with internal combustion engines). The statistics are averages calculated across time and firms, unless specified otherwise. Total emissions is the absolute value of each firm's Scope 1 greenhouse gas emissions in million metric tons of carbon dioxide equivalent ($MmtCO_2e$), and Carbon Intensity is each firm's Scope 1 emissions in metric tons divided by its total revenue in $ million ($mtCO_2e$/$M). Size is the end-of-year market capitalization (in $ million). Age is firm age measured as the number of years since the firm appears in CRSP. BM is the firm's book to market ratio. DY is the dividend yield in % (annual dividends per share divided by the end-of-year stock price). INV is investments scaled by total book assets. OP is operating profits scaled by book equity. VOL is the standard deviation of stock returns over a one-year period from $t-12$ to $t-1$. Beta is the CAPM (market) beta. E Score is the standardized MSCI raw (not-industry adjusted) environmental pillar score. E score coverage is the share of firms with MSCI E scores (in %). $t-$statistics for the differences in means are computed using panel regressions with standard errors clustered on time and firm. $t-$statistics for the differences in medians are computed using panel quantile regressions with standard errors clustered following Parente and Santos Silva (2016). The data are annual and the sample period is from 2016 to 2023.

	Mean				**Median**			
	Heavy emitters	Remaining firms	Δ	$t-$stat	Heavy emitters	Remaining firms	Δ	$t-$stat
Number of firms	277	2491	-	-	273	2451	-	-
Carbon intensity	6.180	0.164	6.017	16.269	4.591	0.095	4.496	26.819
Total emissions	2.290	0.065	2.225	18.241	1.425	0.005	1.420	29.596
Size	15,325	12,111	3,214	1.135	3,219	1,338	1,881	5.476
Age	34	21	13	8.909	27	17	10	6.605
PPE	11,862	1,398	10,464	7.402	3,008	133	2,875	8.987
BM	0.786	0.578	0.208	5.496	0.653	0.441	0.212	10.747
DY	2.543	1.623	0.920	5.441	1.439	0.000	1.439	21.661
INV	0.101	0.133	-0.032	-0.971	0.046	0.054	-0.008	-0.663
OP	0.220	0.103	0.117	2.963	0.194	0.176	0.019	2.657
VOL	13.257	13.512	-0.254	-0.333	10.433	10.880	-0.447	-1.061
Beta	1.373	1.198	0.175	3.171	1.207	1.083	0.124	2.642
E score	-1.486	0.186	-1.673	-22.457	-1.624	0.308	-1.932	-20.447
E score coverage	79.870	71.130	8.700	5.445	81.790	70.520	7.000	1.340

Table 2: Heavy emitters share of Fama-French portfolios

This table presents market capitalization share of heavy emitters in Fama-French characteristic-sorted portfolios. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers). The relevant sorts for five Fama-French factors are considered: SMB (Size), HML (Book-to-Market), RMW (Operating Profitability), CMA (Investment), and WML (Momentum). Portfolio sorting procedure follows Fama and French (1993, 2015). Two SMB portfolios are formed by sorting stocks into two buckets on size (Small and Big) using the NYSE median as the cutoff. HML, RMW, CMA, and WML portfolios are formed by first sorting on size and then sorting on the relevant characteristic (e.g., book-to-market) into three groups (Long, Neutral, and Short). Portfolios are re-balanced annually. Each panel of the table reports portfolio shares for each year in the main sample (2016–2023) and the average share across those years (mean). Also reported are the average shares across the extended sample (2005–2023) that uses backfilled emissions data in the years prior 2016 if none is available to identify the heavy emitters. For the individual portfolios, t-statistics for the test of the mean weight being different from the unconditional sample mean for the size-sorted portfolios or the conditional sample mean ($\bar{w}_v^k$, where k = Small or Big) for the other sorts are reported. For example, in the case of Small Value portfolio in the main sample the t-test compares the share to 9% (i.e., the conditional mean for Small stocks in Panel A). For the difference between Long and Short shares and each factor, the t-statistics for the test of the mean being different from zero are reported. The data are annual and the main sample period is from 2016 to 2023.

Panel A: SMB (Size)

	Portfolios						Difference	Factor
	Long					**Short**	**Long−Short**	
								SMB
	Small					Big		
2016	0.07	-	-	-	-	0.16	-0.09	-0.09
2017	0.08	-	-	-	-	0.15	-0.06	-0.06
2018	0.07	-	-	-	-	0.15	-0.07	-0.07
2019	0.08	-	-	-	-	0.13	-0.05	-0.05
2020	0.08	-	-	-	-	0.10	-0.02	-0.02
2021	0.11	-	-	-	-	0.11	0.00	0.00
2022	0.10	-	-	-	-	0.14	-0.05	-0.05
2023	0.09	-	-	-	-	0.12	-0.02	-0.02
mean	0.08	-	-	-	-	0.13	-0.05	-0.05
t-stat ($x = 0.123$)	(-8.05)	-	-	-	-	(1.14)	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-16.29)	(-16.29)
Backfilled emissions sample (2005–2023)								
mean	0.07	-	-	-	-	0.15	-0.08	-0.08
t-stat ($x = 0.139$)	(-17.02)	-	-	-	-	(2.23)	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-25.55)	(-25.55)

Table 2: Heavy emitters share of Fama-French portfolios (continued)

Panel B: HML (Book-to-Market)

	Portfolios						Difference		Factor
	Long *Value*		**Neutral**		**Short** *Growth*		**Long−Short**		*HML*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.13	0.36	0.06	0.26	0.03	0.02	0.09	0.34	0.22
2017	0.13	0.35	0.07	0.21	0.05	0.03	0.08	0.31	0.20
2018	0.12	0.40	0.08	0.26	0.04	0.02	0.08	0.37	0.23
2019	0.15	0.30	0.07	0.29	0.02	0.03	0.13	0.27	0.20
2020	0.15	0.40	0.07	0.22	0.04	0.03	0.11	0.36	0.24
2021	0.17	0.39	0.11	0.18	0.06	0.03	0.11	0.36	0.23
2022	0.14	0.50	0.11	0.20	0.04	0.04	0.10	0.46	0.28
2023	0.13	0.31	0.09	0.23	0.05	0.05	0.08	0.26	0.17
mean	0.14	0.37	0.08	0.23	0.04	0.03	0.10	0.34	0.22
t-stat ($x = \bar{w}_v^k$)	(10.02)	(10.97)	(-0.31)	(8.13)	(-9.97)	(-34.78)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(15.62)	(15.00)	(18.09)
Backfilled emissions sample (2005–2023)									
mean	0.12	0.34	0.07	0.24	0.04	0.06	0.09	0.28	0.18
t-stat ($x = \bar{w}_v^k$)	(7.85)	(9.38)	(-0.19)	(8.31)	(-11.65)	(-13.27)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(12.52)	(12.52)	(13.24)

Table 2: Heavy emitters share of Fama-French portfolios (continued)

Panel C: CMA (Investment)

	Portfolios						Difference		Factor
	Long *Conservative*		**Neutral**		**Short** *Aggressive*		**Long−Short**		*CMA*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.15	0.17	0.06	0.20	0.03	0.08	0.12	0.09	0.10
2017	0.11	0.22	0.06	0.13	0.08	0.13	0.03	0.09	0.06
2018	0.09	0.15	0.08	0.19	0.07	0.10	0.02	0.05	0.04
2019	0.07	0.04	0.08	0.23	0.07	0.07	-0.00	-0.03	-0.02
2020	0.12	0.10	0.08	0.13	0.06	0.08	0.06	0.02	0.04
2021	0.17	0.16	0.14	0.18	0.05	0.02	0.12	0.15	0.14
2022	0.10	0.16	0.10	0.17	0.09	0.06	0.01	0.09	0.05
2023	0.03	0.05	0.11	0.16	0.13	0.09	-0.10	-0.04	-0.07
mean	0.10	0.13	0.09	0.17	0.07	0.08	0.03	0.05	0.04
t-stat ($x = \bar{w}_v^k$)	(1.25)	(-0.06)	(0.53)	(3.41)	(-1.23)	(-4.73)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(1.28)	(2.22)	(1.84)
Backfilled emissions sample (2005–2023)									
mean	0.08	0.13	0.08	0.20	0.07	0.11	0.01	0.02	0.01
t-stat ($x = \bar{w}_v^k$)	(0.42)	(-2.22)	(0.81)	(4.39)	(-1.00)	(-3.63)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(0.72)	(1.14)	(1.09)

Panel D: RMW (Operating Profitability)

	Portfolios						Difference		Factor
	Long *Robust*		**Neutral**		**Short** *Weak*		**Long−Short**		*RMW*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.08	0.07	0.04	0.10	0.09	0.45	-0.01	-0.38	-0.19
2017	0.07	0.06	0.07	0.10	0.10	0.47	-0.03	-0.41	-0.22
2018	0.12	0.05	0.08	0.16	0.06	0.45	0.06	-0.40	-0.17
2019	0.16	0.06	0.08	0.17	0.04	0.29	0.13	-0.23	-0.05
2020	0.11	0.06	0.09	0.17	0.06	0.14	0.05	-0.08	-0.02
2021	0.09	0.05	0.10	0.17	0.13	0.19	-0.03	-0.14	-0.09
2022	0.19	0.07	0.09	0.28	0.06	0.09	0.13	-0.01	0.06
2023	0.20	0.10	0.09	0.12	0.05	0.21	0.15	-0.12	0.02
mean	0.13	0.07	0.08	0.16	0.07	0.29	0.06	-0.22	-0.08
t-stat ($x = \bar{w}_v^k$)	(2.47)	(-12.12)	(-1.06)	(1.42)	(-0.99)	(2.88)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(2.06)	(-3.99)	(-2.27)
Backfilled emissions sample (2005–2023)									
mean	0.09	0.12	0.07	0.16	0.07	0.25	0.03	-0.13	-0.05
t-stat ($x = \bar{w}_v^k$)	(1.98)	(-2.36)	(-0.36)	(0.38)	(-1.30)	(3.82)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(2.24)	(-3.96)	(-2.82)

Table 2: Heavy emitters share of Fama-French portfolios (continued)

Panel E: WML (Momentum)

	Portfolios						Difference		Factor
	Long *Winners*		**Neutral**		**Long** *Losers*		**Long−Short**		*WML*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.10	0.19	0.04	0.14	0.06	0.13	0.03	0.06	0.05
2017	0.05	0.06	0.06	0.24	0.13	0.16	-0.07	-0.10	-0.09
2018	0.07	0.08	0.09	0.19	0.09	0.16	-0.02	-0.08	-0.05
2019	0.05	0.07	0.07	0.15	0.13	0.32	-0.08	-0.25	-0.17
2020	0.07	0.06	0.06	0.13	0.10	0.32	-0.03	-0.26	-0.15
2021	0.12	0.09	0.09	0.12	0.08	0.08	0.04	0.01	0.02
2022	0.17	0.27	0.08	0.10	0.03	0.02	0.14	0.25	0.19
2023	0.06	0.07	0.10	0.16	0.07	0.17	-0.01	-0.10	-0.06
mean	0.09	0.11	0.08	0.15	0.09	0.17	-0.00	-0.06	-0.03
t-stat ($x = \bar{w}_v^k$)	(0.14)	(-0.76)	(-1.31)	(1.46)	(0.23)	(1.04)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-0.03)	(-1.00)	(-0.73)
Backfilled emissions sample (2005–2023)									
mean	0.07	0.13	0.07	0.16	0.08	0.17	-0.01	-0.04	-0.02
t-stat ($x = \bar{w}_v^k$)	(-0.36)	(-1.12)	(-0.69)	(0.69)	(0.32)	(0.91)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-0.43)	(-1.07)	(-0.94)

Table 3: Heavy emitters share of Fama-French-type anomaly portfolios

This table presents market capitalization share of heavy emitters in Fama-French-type characteristic-sorted anomaly portfolios from Chen and Zimmermann (2021). Specifically, anomaly portfolios that are reasonably related to value (panel A), investment (panel B), and profitability (panel C) are considered. For each anomaly, either five or ten portfolios are formed each period by sorting on a given characteristic. Portfolio 1 is always the short leg, while Portfolio 5 or 10 is the long leg. 'Sort' indicates whether the sorting is from low to high or from high to low values of the characteristic. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample. The table reports the average share across the years of the main sample (2016–2023) and the average share across the extended sample (2005–2023), which uses backfilled emissions data for the years prior to 2016 when no data is available. t-statistics for the test of the mean being different from 10% are reported for individual portfolios. For the difference between Long and Short shares (L−S), the t-statistics for the test of the mean being different from zero are reported. The data are annual and the main sample period is from 2016 to 2023. Panel A reports portfolios formed on the following characteristics: (i) intangible return (using cash flow to price) from Daniel and Titman (2006); (ii) cash productivity from Chandrashekar and Rao (2009); (iii) enterprise multiple from Loughran and Wellman (2011); (iv) operating cash flow to price from Desai et al. (2004); (v) cash flow to market value from Lakonishok, Shleifer, and Vishny (1994); (vi) sales-to-price from Barbee, Mukherji, and Raines (1996); (vii) long-term EPS forecast La Porta (1996); and (viii) employment growth from Belo et al. (2014).

Name	Citation	Sort	Sample	1	2	3	4	5	6	7	8	9	10	L−S
Panel A: Value														
Intangible return using CFtoP	Daniel & Titman (2006)	High to low	2016–2023	0.03	0.11	0.15	0.20	0.37	-	-	-	-	-	0.33
				(-15.28)	(-1.40)	(0.67)	(2.99)	(6.15)	-	-	-	-	-	(7.90)
			2005–2023	0.10	0.13	0.13	0.17	0.27	-	-	-	-	-	0.17
				(-1.95)	(-0.71)	(-0.71)	(1.65)	(3.51)	-	-	-	-	-	(3.13)
Cash productivity	Chandrashekar & Rao (2009)	High to low	2016–2023	0.06	0.08	0.15	0.22	0.34	-	-	-	-	-	0.28
				(-6.51)	(-1.57)	(0.93)	(6.40)	(11.42)	-	-	-	-	-	(11.14)
			2005–2023	0.09	0.10	0.16	0.20	0.32	-	-	-	-	-	0.22
				(-4.48)	(-3.02)	(1.34)	(4.78)	(10.31)	-	-	-	-	-	(10.26)
Enterprise multiple	Loughran & Wellman (2011)	High to low	2016–2023	0.02	0.03	0.10	0.17	0.19	0.23	0.19	0.21	0.18	0.22	0.20
				(-15.86)	(-10.15)	(-1.39)	(2.10)	(2.73)	(2.51)	(1.82)	(1.48)	(1.40)	(2.13)	(4.48)
			2005–2023	0.03	0.03	0.07	0.12	0.16	0.20	0.20	0.26	0.28	0.24	0.21
				(-20.23)	(-20.39)	(-6.72)	(-1.59)	(0.75)	(3.07)	(2.68)	(3.25)	(4.16)	(3.01)	(6.22)
Operating cash flows to price	Desai et al. (2004)	Low to high	2016–2023	0.06	0.02	0.06	0.24	0.26	-	-	-	-	-	0.20
				(-4.24)	(-16.11)	(-6.41)	(7.56)	(6.79)	-	-	-	-	-	(6.45)
			2005–2023	0.05	0.03	0.07	0.25	0.27	-	-	-	-	-	0.22
				(-9.96)	(-26.44)	(-7.72)	(6.82)	(7.49)	-	-	-	-	-	(10.08)
Cash flow to market	Lakonishok et al. (1994)	Low to high	2016–2023	0.26	0.21	0.05	0.06	0.11	0.19	0.34	0.32	0.34	0.51	0.24
				(0.84)	(0.33)	(-7.35)	(-11.79)	(-3.24)	(0.32)	(3.80)	(2.19)	(3.46)	(5.11)	(1.89)
			2005–2023	0.17	0.16	0.06	0.05	0.10	0.16	0.30	0.33	0.40	0.46	0.29
				(-0.63)	(-1.13)	(-11.97)	(-21.92)	(-8.27)	(-2.14)	(3.72)	(3.75)	(5.52)	(6.85)	(4.92)
Sales-to-price	Barbee et al. (1996)	Low to high	2016–2023	0.02	0.08	0.16	0.25	0.22	-	-	-	-	-	0.20
				(-9.98)	(-6.07)	(3.15)	(10.84)	(6.28)	-	-	-	-	-	(9.89)
			2005–2023	0.04	0.10	0.19	0.26	0.19	-	-	-	-	-	0.15
				(-13.76)	(-5.68)	(2.98)	(8.14)	(4.02)	-	-	-	-	-	(8.46)
Long-term EPS forecast	La Porta (1996)	High to low	2016–2023	0.13	0.06	0.06	0.09	0.23	-	-	-	-	-	0.09
				(0.88)	(-3.24)	(-3.20)	(-1.97)	(3.46)	-	-	-	-	-	(1.67)
			2005–2023	0.11	0.08	0.08	0.10	0.28	-	-	-	-	-	0.17
				(-1.99)	(-6.76)	(-4.79)	(-7.56)	(7.21)	-	-	-	-	-	(5.51)
Employment growth	Bazdresch et al. (2014)	High to low	2016–2023	0.03	0.06	0.16	0.19	0.22	-	-	-	-	-	0.19
				(-14.94)	(-7.23)	(2.93)	(3.42)	(5.45)	-	-	-	-	-	(11.20)
			2005–2023	0.05	0.11	0.16	0.22	0.18	-	-	-	-	-	0.13
				(-16.32)	(-2.75)	(1.98)	(4.47)	(2.68)	-	-	-	-	-	(7.59)

Table 3: Heavy emitters share of Fama-French-type anomaly portfolios (continued)

Panels A (continued), B and C report portfolios formed on the following characteristics: (ix) implied equity duration from Dechow et al. (2004); (x) tangibility from Hahn and Lee (2009); (xi predicited dividend yield in the next month from Litzenberger and Ramaswamy (1979b); (xii) asset growth from Cooper et al. (2008); (xiii) change in capex from Anderson and Garcia-Feijoo (2006); (xiv) investment to revenue from Titman et al. (2004); (xv) gross profits over total assets from Novy-Marx (2013); (xvi) taxable income to income from Lev and Nissim (2004); and (xvii) R&D adjusted profitability from Ball et al. (2016). Exact definitions can be found in Chen and Zimmermann (2021).

Name	Citation	Sort	Sample	1	2	3	4	5	6	7	8	9	10	L−S
Panel A: Value (continued)														
Equity duration	Dechow et al. (2004)	High to low	2016–2023	0.10	0.03	0.13	0.31	0.21	-	-	-	-	-	0.11
				(-0.78)	(-16.50)	(0.29)	(8.62)	(4.09)	-	-	-	-	-	(3.67)
			2005–2023	0.10	0.05	0.14	0.31	0.20	-	-	-	-	-	0.10
				(-3.48)	(-17.03)	(-0.34)	(9.61)	(3.23)	-	-	-	-	-	(4.22)
Tangibility	Hahn & Lee (2009)	Low to high	2016–2023	0.01	0.10	0.12	0.56	0.11	-	-	-	-	-	0.10
				(-26.78)	(-0.85)	(0.79)	(9.79)	(0.13)	-	-	-	-	-	(8.03)
			2005–2023	0.02	0.09	0.14	0.53	0.27	-	-	-	-	-	0.26
				(-49.02)	(-5.57)	(0.08)	(10.22)	(2.05)	-	-	-	-	-	(3.92)
Predicted div yield next month	Litzenberger & Ramaswamy (1979)	Low to high	2016–2023	0.14	0.09	0.12	0.20	-	-	-	-	-	-	0.06
				(0.38)	(-3.03)	(-1.87)	(7.05)	-	-	-	-	-	-	(9.22)
			2005–2023	0.17	0.12	0.13	0.18	-	-	-	-	-	-	0.01
				(1.08)	(-2.89)	(-2.97)	(1.23)	-	-	-	-	-	-	(0.37)
Panel B: Investment														
Asset growth	Cooper et al. (2008)	High to low	2016–2023	0.05	0.05	0.09	0.12	0.16	0.15	0.21	0.11	0.12	0.15	0.10
				(-5.05)	(-4.51)	(-2.21)	(-0.22)	(1.70)	(2.58)	(2.73)	(-0.28)	(0.09)	(0.44)	(1.55)
			2005–2023	0.07	0.07	0.14	0.14	0.20	0.19	0.18	0.11	0.12	0.16	0.09
				(-9.14)	(-4.41)	(-0.28)	(-0.03)	(2.56)	(2.41)	(2.06)	(-2.08)	(-1.35)	(0.57)	(3.05)
Change in capex (three years)	Anderson & Garcia-Feijoo (2006)	High to low	2016–2023	0.05	0.10	0.14	0.20	0.21	-	-	-	-	-	0.16
				(-9.41)	(-2.10)	(0.57)	(2.33)	(1.46)	-	-	-	-	-	(2.71)
			2005–2023	0.10	0.17	0.17	0.13	0.11	-	-	-	-	-	0.00
				(-2.86)	(0.85)	(1.68)	(-0.98)	(-1.40)	-	-	-	-	-	(0.10)
Investment to revenue	Titman et al. (2004)	High to low	2016–2023	0.13	0.13	0.09	0.18	0.19	-	-	-	-	-	0.06
				(-0.08)	(-0.04)	(-5.84)	(1.62)	(1.53)	-	-	-	-	-	(1.11)
			2005–2023	0.20	0.16	0.12	0.15	0.11	-	-	-	-	-	-0.09
				(1.98)	(0.85)	(-3.20)	(0.12)	(-1.85)	-	-	-	-	-	(-2.14)
Panel C: Profitability														
Gross profits / total assets	Novy-Marx (2013)	Low to high	2016–2023	0.44	0.44	0.14	0.03	0.01	-	-	-	-	-	-0.43
				(2.86)	(14.08)	(-0.12)	(-15.71)	(-52.75)	-	-	-	-	-	(-4.16)
			2005–2023	0.48	0.39	0.14	0.04	0.01	-	-	-	-	-	-0.47
				(6.44)	(10.94)	(-1.11)	(-11.37)	(-56.18)	-	-	-	-	-	(-9.69)
Taxable income to income	Lev & Nissim (2004)	Low to high	2016–2023	0.43	0.10	0.07	0.15	0.11	-	-	-	-	-	-0.32
				(10.36)	(-2.93)	(-5.67)	(0.60)	(-0.97)	-	-	-	-	-	(-7.50)
			2005–2023	0.36	0.11	0.09	0.12	0.23	-	-	-	-	-	-0.14
				(8.25)	(-5.31)	(-6.60)	(-1.90)	(2.52)	-	-	-	-	-	(-2.67)
Operating profitability R&D adjusted	Ball et al. (2016)	Low to high	2016–2023	0.20	0.24	0.23	0.18	0.14	0.16	0.12	0.09	0.07	0.01	-0.19
				(1.34)	(2.05)	(2.47)	(2.72)	(1.32)	(2.38)	(0.93)	(-0.07)	(-1.72)	(-15.64)	(-2.29)
			2005–2023	0.17	0.18	0.21	0.18	0.14	0.15	0.15	0.14	0.10	0.06	-0.11
				(1.18)	(1.70)	(3.26)	(3.83)	(0.85)	(1.01)	(1.77)	(0.85)	(-0.85)	(-3.23)	(-2.50)

Table 4: Carbon intensity, absolute emissions, and E scores of book-to-market-sorted portfolios

This table presents value-weighted portfolio carbon intensities, absolute Scope 1 emissions, and MSCI E scores for the Fama-French Big Value (BV) and Big Growth (BG) portfolios, and their differences. Fama-French portfolios are defined in Table 2. Each Fama-French portfolio is further separated into heavy and light emitter portfolios. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. For the purpose of categorization carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in mtCO_2e/$M). Scope 1 measures only direct emissions from production. Scope 2 measures direct emissions from consumption of purchased electricity, heat, or steam. Upstream Scope 3 measures emissions not produced by the company itself, but that are part of its value chain. The different emission measures are: Scope 1 carbon intensity, Scope 1 and 2 carbon intensity, Scope 1, 2, and upstream Scope 3 carbon intensity, absolute Scope 1 emissions (measured in MmtCO_2e), and standardized MSCI E scores, where a lower score indicates a worse score (more polluting). t-statistics for the test of the mean being different from zero are reported. The data are annual and the main sample period is from 2016 to 2023.

					Difference	
Measure	Sample	Big Value heavy	Big Value light	Big Growth light	BV heavy − BV light	BV light − BG light
Carbon intensity (Scope 1)	2016–2023	3.876	0.080	0.116	3.797	-0.036
		-	-	-	(6.941)	(-1.616)
	2005–2023	4.946	0.114	0.165	4.832	-0.052
		-	-	-	(10.715)	(-4.037)
Carbon intensity (Scope 1 + 2)	2016–2023	4.477	0.232	0.294	4.244	-0.062
		-	-	-	(7.573)	(-1.484)
	2005–2023	5.708	0.265	0.399	5.443	-0.134
		-	-	-	(10.239)	(-5.037)
Carbon intensity (Scope 1, 2, + 3)	2016–2023	7.570	1.090	1.479	6.480	-0.389
		-	-	-	(9.856)	(-3.975)
	2005–2023	8.343	1.126	1.791	7.217	-0.665
		-	-	-	(15.272)	(-7.515)
Absolute Scope 1 emissions	2016–2023	28.954	0.256	0.916	28.698	-0.660
		-	-	-	(4.177)	(-8.319)
	2005–2023	25.745	0.375	0.783	25.370	-0.408
		-	-	-	(6.884)	(-4.268)
MSCI E scores	2016–2023	-1.532	0.637	0.424	-2.169	0.214
		-	-	-	(-15.155)	(3.142)
	2012–2023	-1.484	0.672	0.443	-2.156	0.229
		-	-	-	(-20.542)	(4.619)

Table 5: Big Value and Big Growth realized returns and implied cost of capital

This table presents linear regressions of value-weighted portfolio return differences and ICC differences on time period dummies. Post Paris is a dummy variable equal to one after December 2015 (Paris climate meeting) and zero otherwise. Post 2021 is a dummy variable equal to one during the high-inflation years of 2021 and 2022, and zero otherwise. Panel A reports the results for the realized returns, and Panel B reports the results for the ICCs. In both panels, columns (1)-(3) present the results for the difference between the Big Value heavy emitters and Big Value light emitters portfolios, while columns (4)-(6) present the results for the difference between the Big Value light emitters and Big Growth light emitters portfolios. Fama-French portfolios are defined in Table 2. Each Fama-French portfolio is further separated into heavy and light emitter portfolios. Heavy emitters are defined as the top 10% of the most carbon-intensive firms in the CRSP sample each year (with the five least carbon-intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. ICC is measured as the average of four ICC estimates using the methodologies of Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), following Mohanram and Gode (2013) and Eskildsen et al. (2024). Portfolio ICCs are computed as value-weighted (equal-weighted) averages of monthly ICCs of stocks within each portfolio. All returns are annualized and are in %. t-statistics based on Newey and West (1987) standard errors are reported in parentheses (the lag length is selected automatically using the Newey and West (1994) procedure). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The return series are monthly, and the sample period runs from July 2005 to December 2023, with the ICC series ending in December 2022.

Panel A: Returns

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.26	1.30	1.30	−3.35	−1.39	−1.39
	(0.86)	(0.20)	(0.26)	(−0.91)	(−0.29)	(−0.39)
Post 2016		6.83	−3.27		−4.54	−10.20*
		(0.69)	(−0.38)		(−0.61)	(−1.65)
Post 2021			40.39***			22.64**
			(2.81)			(2.13)
Observations	222	222	222	222	222	222

Panel B: ICC

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.01	−0.43	−0.43	2.87***	2.35***	2.35***
	(−0.02)	(−1.21)	(−1.22)	(9.30)	(8.01)	(9.05)
Post Paris		1.07*	1.13*		1.31***	1.02**
		(1.91)	(1.85)		(2.88)	(2.31)
Post 2021			−0.23			0.99
			(−0.26)			(1.57)
Observations	210	210	210	210	210	210

Table 6: Big Value and Big Growth realized risk-adjusted returns

This table presents linear time-series regressions of value-weighted portfolio return differences on Fama and French factors. The dependent variable are the return differences between the Big Value heavy emitters and light emitters in columns (1)-(3), and between the Big Value light emitters and Big Growth emitters in columns (4)-(6). These portfolios are defined in Table 5. The explanatory variables include the Fama-French factors MKT (Market), SMB (Size), CMA (Investment), and RMW (Operating Profitability). We omit the HML (Book-to-Market) factor, as the Value and Growth portfolios are used in its construction. All returns are annualized and are in %. *t*-statistics based on Newey and West (1987) standard errors are reported in parentheses (the lag length is selected automatically using the Newey and West (1994) procedure). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The return series are monthly, and the sample period runs from July 2005 to December 2023.

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.26	3.80	1.03	−3.35	−6.29**	−5.18**
	(0.86)	(0.75)	(0.24)	(−1.16)	(−2.32)	(−2.42)
MKT		0.05	0.05		0.31***	0.29***
		(0.64)	(0.64)		(5.15)	(5.26)
SMB			0.39**			0.24**
			(2.52)			(2.26)
CMA			0.54***			0.91***
			(3.16)			(7.82)
RMW			0.55***			−0.41***
			(2.79)			(−3.05)
Observations	222	222	222	222	222	222
R-squared	0.00	0.00	0.09	0.00	0.12	0.35

Figure 1: Carbon intensity across industries

This figure shows the distribution of average carbon intensities across industries. Carbon intensity is defined as Scope 1 greenhouse gas emissions in metric tons of carbon dioxide equivalent divided by the firm's total revenue in \$ million (mtCO_2e/\$M). Scope 1 measures only direct emissions from production. The box encapsulates the inter-quantile range, with the median indicated in green. Plots' whiskers delineate the 2.5% and 97.5% percentiles. For the Utils and Mines sectors, the top whisker is equal to 52 and 43, respectively, but are omitted to facilitate exposition. Industries are categorized into the 12 Fama and French groups: Consumer Non-Durables (NoDur), Consumer Durables (Durbl), Manufacturing (Manuf), Energy (Enrgy), Chemicals (Chems), Business Equipment (BusEq), Telecommunications (Telcm), Utilities (Utils), Shops (Shops), Healthcare (Hlth), Finance (Fin), and Other. Other industry grouping is further divided into Mining (Mines), Transport (Trans), Construction (Cnstr), and Hotels and Entertainment (HotEnt). Agriculture (Ag) is separated out of NoDur and presented separately. Five largest technology firms, denoted as FAAMG (Facebook/Meta, Amazon, Apple, Microsoft, and Google/Alphabet), and Berkshire Hathaway (denoted as BRK) are presented separately. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

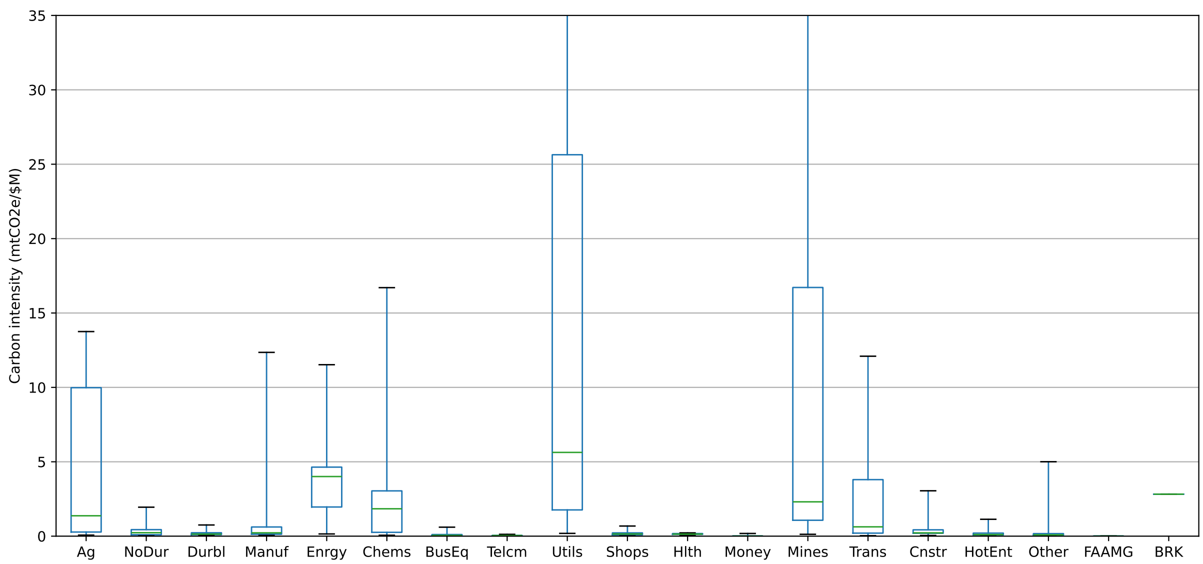
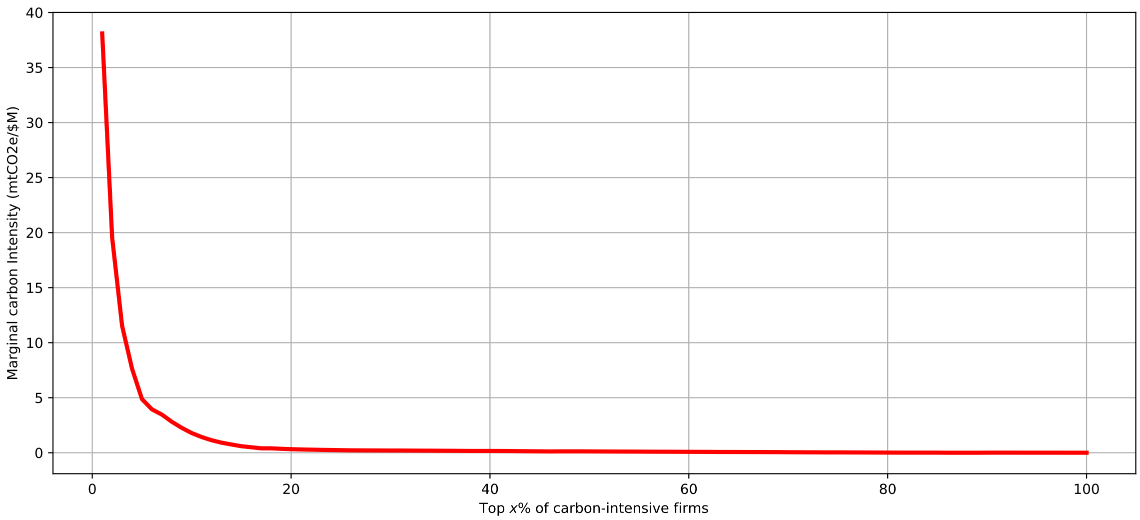


Figure 2: Marginal carbon intensity

This figure shows the marginal carbon intensity of top x% of firms ranked by their carbon intensity. Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in mtCO_2e/\$M). Scope 1 measures only direct emissions from production. Panel (a) shows the full range, from 0% to 100%, while Panel (b) zooms in the four key cutoffs, 5%, 10%, 15%, and 20% of the most carbon-intensive firms. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

(a)



(b)

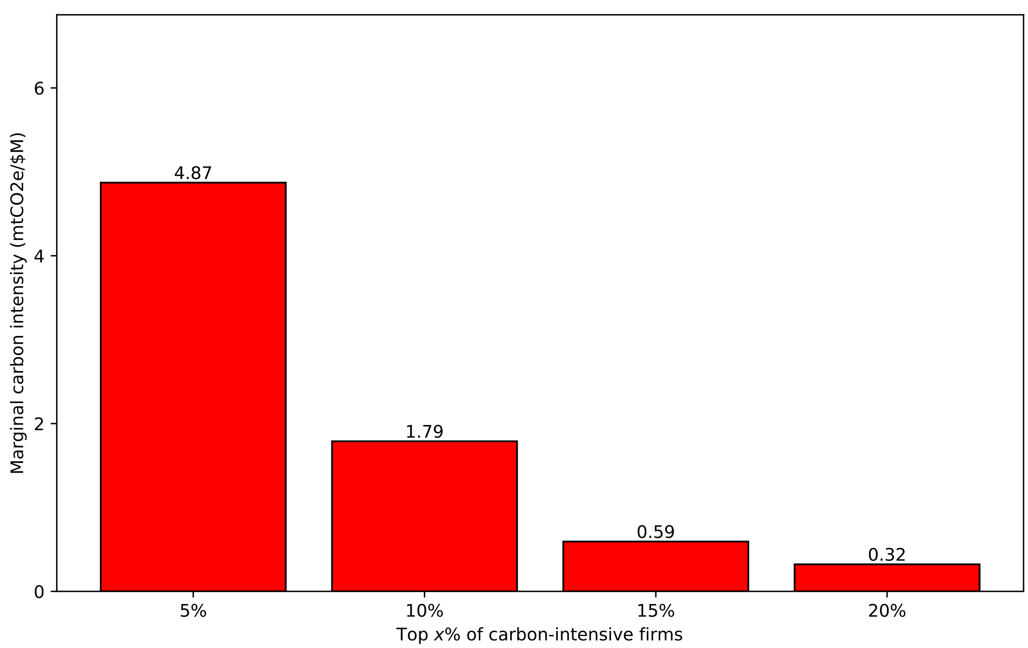
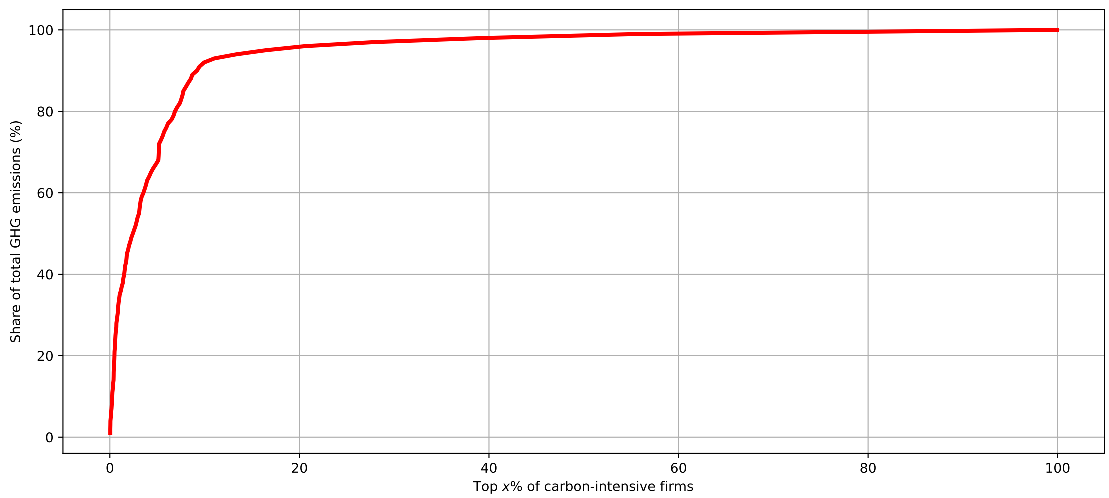


Figure 3: Contribution to aggregate GHG emissions

This shows the percentage of total GHG emissions from US public firms accounted for by the top x% of firms ranked by their carbon intensity. Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in mtCO_2e/\$M). Scope 1 measures only direct emissions from production. Firms are ranked by their carbon intensities each year (from highest to lowest). The reported figures are averages across the sample period. Panel (a) shows the full range, from 0% to 100%, while Panel (b) zooms in the four key cutoffs, 5%, 10%, 15%, and 20% of the most carbon-intensive firms. Panel (b) also shows the share of aggregate market capitalization accounted for by the the top x% carbon-intensitve firms. The data are annual and the sample period is from 2016 to 2023.

(a)



(b)

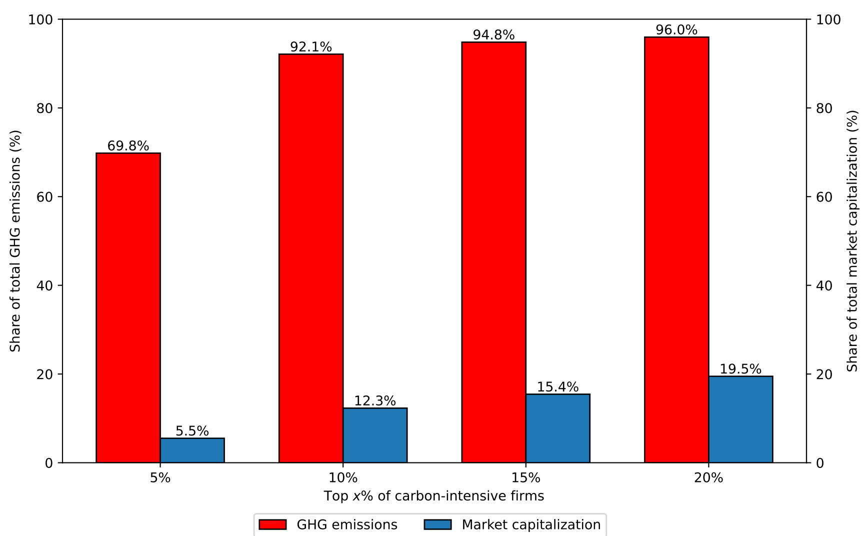
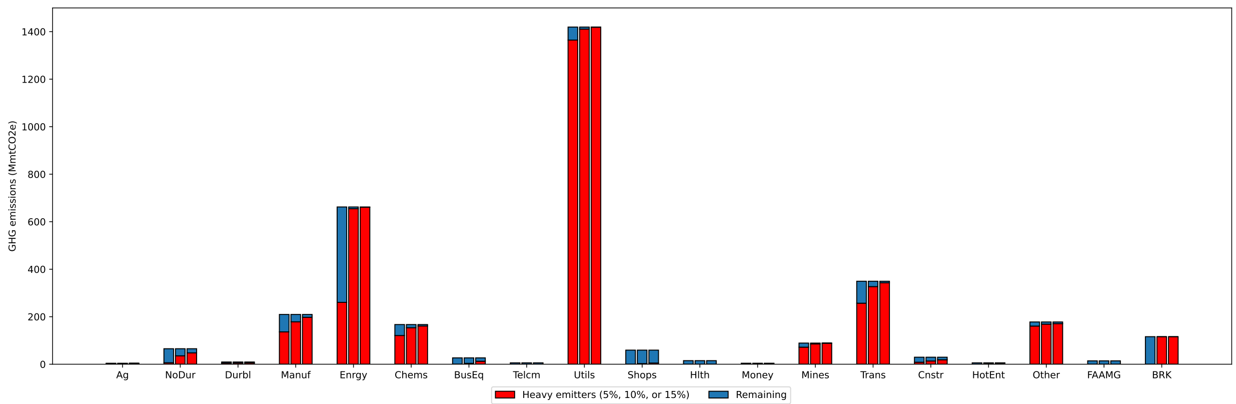


Figure 4: Emissions and market capitalization of heavy emitters by industry

This figure shows the (a) total GHG emissions (measured in million mtCO_2e) and (b) market capitalization corresponding to the top 5%, top 10%, and top 15% of firms sorted on carbon intensity. Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in mtCO_2e/\$M). Industry categories are explained in Figure 1. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

(a) Emissions



(b) Market capitalization

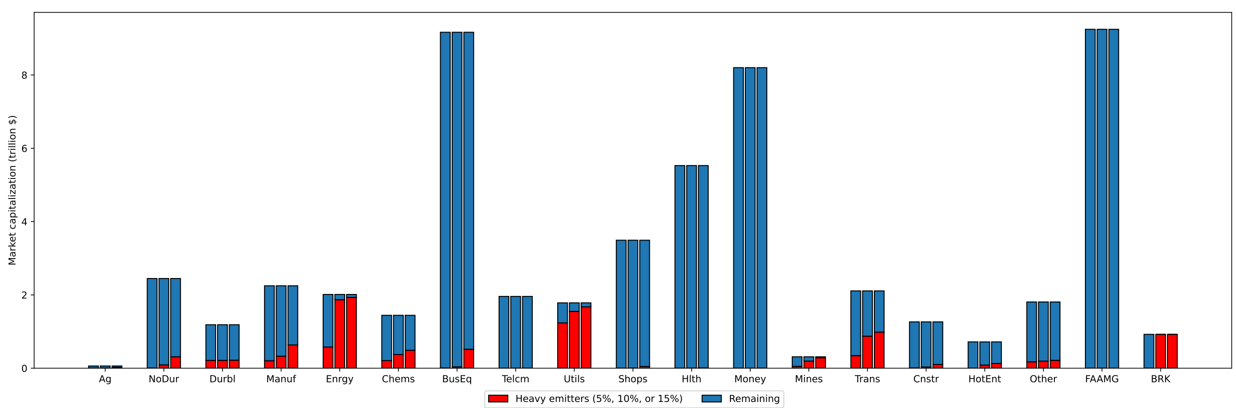


Figure 5: Persistence of carbon-intensity rankings

This figure shows transition probabilities for firms sorted on carbon intensity. Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in mtCO_2e/\$M). Each year, firms are assigned to deciles based on their carbon intensity, with decile 1 (0%–10%) containing the firms with the lowest carbon intensity and decile 10 (90%–100%) the firms with the highest. Transition probability, $p(j, i)$, for firms moving from one decile to another between two subsequent years is calculated as a fraction of firms moving from decile j to i. The plot shows the average of these transition probabilities over the sample period 2016–2023. The bars in cell (Current, Previous) represent the conditional probability of achieving a current ranking of decile j, given a ranking of decile i in the previous year.

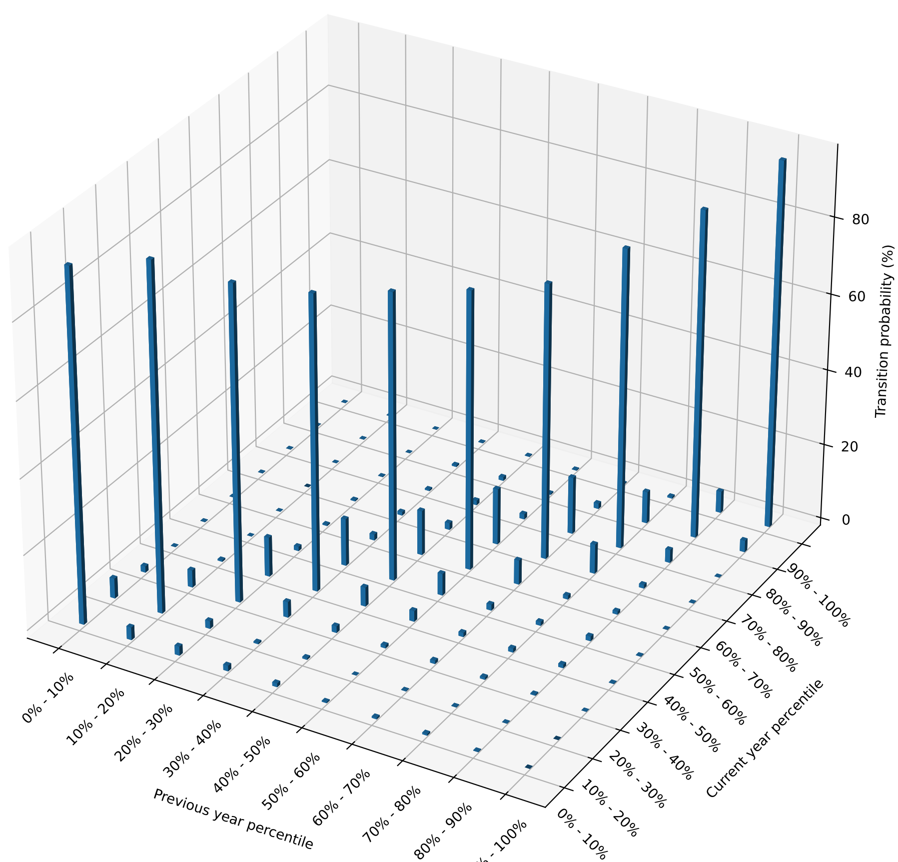


Figure 6: Carbon-intensity rankings and E scores

This figure shows scatter plot of carbon intensity ranks versus standardized E scores. Heavy emitters (top 10% of most carbon intensive firms) are highlighted in red and other firms in blue. The ranks and E scores are averages over the sample period. Lower E scores correspond to poorer environmental scores. The regression line illustrates the relationship between carbon intensity and E scores. The data are annual and the sample period is from 2016 to 2023.

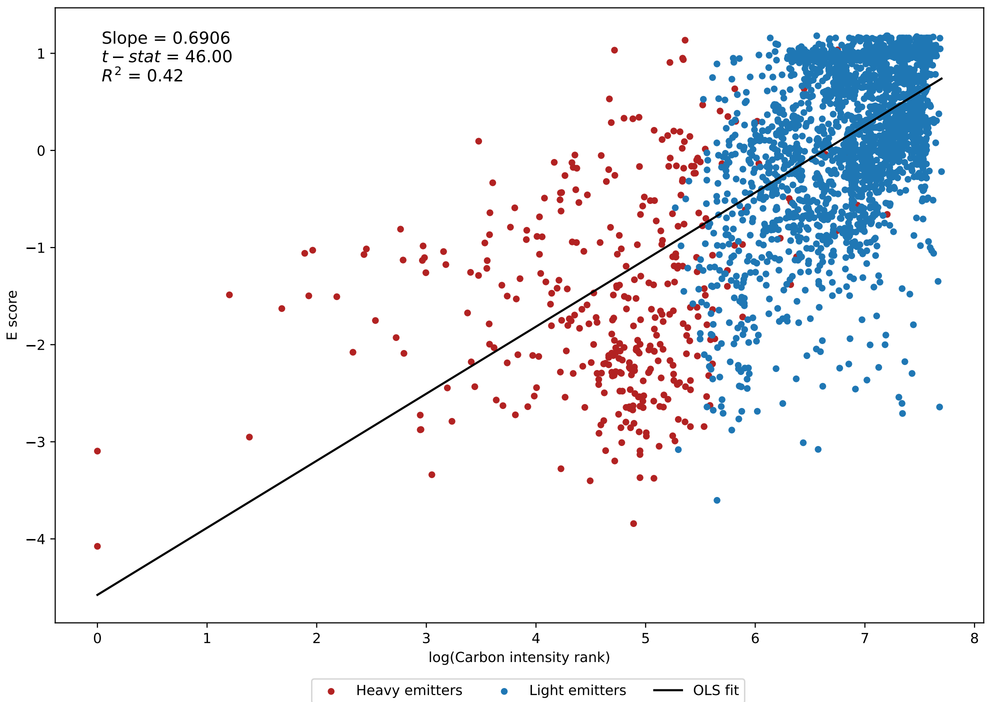


Figure 7: Heavy emitters' investments vs commodity prices

This figure shows the time series of aggregate investment (INV) vs Goldman Sachs Commodity Index (GSCI) for heavy and low emitters. Heavy emitters are defined as the top 10% most carbon-intensive firms in the CRSP sample, while light emitters are firms that do not fall into this category. The data are annual and the sample period is from 2005 to 2023.

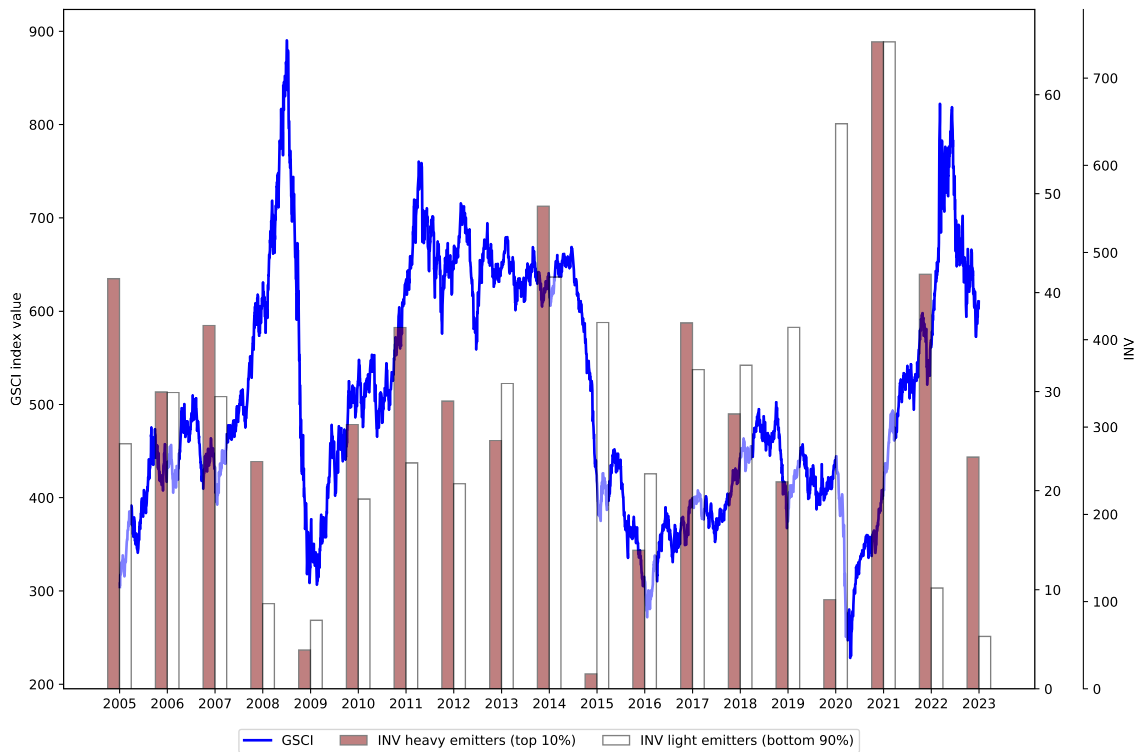
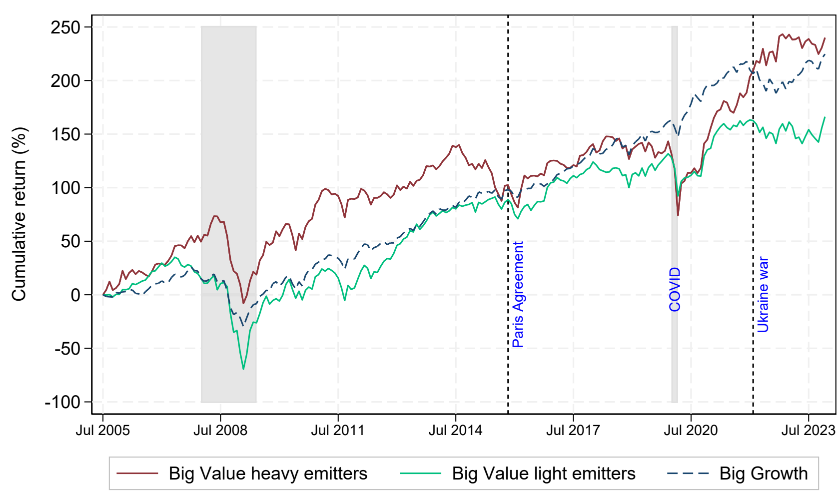


Figure 8: Realized returns of heavy and light emitters of the Big Value portfolio

This figure shows the returns of the two sub-portfolios that comprise the Big Value portfolio: Big Value heavy emitters and Big Value light emitters. The Big Value portfolio is a long-only portfolio constructed following the method outlined on Ken French's website. Stocks are first sorted into two groups based on size (Small and Big) and then into tertiles based on book-to-market equity. The Big Value portfolio consists of the big stocks in the highest book-to-market tertile. The Big Growth portfolio, consisting of stocks in the lowest book-to-market tertile, is also plotted. Heavy emitters are defined as the top 10% most carbon-intensive firms in the CRSP sample (with the five least carbon-intensive firms substituted for the five firms producing vehicles with internal combustion engines), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. Panel (a) shows the cumulative value-weighted returns. Panel (b) shows the cumulative return spread (in %) between heavy and light emitters in the Big Value portfolio, together with the GSCI return index. The shaded area denotes NBER recessions. The vertical dashed lines denote the Paris climate meeting in December 2015 and the start of the Ukraine war in February 2022. The return series are monthly, and the sample period runs from July 2005 to December 2023 (in the years prior to 2016, backfilled emissions data are used to identify heavy emitters when no data is available).

(a) Big Value performance



(b) Big Value emitter spread

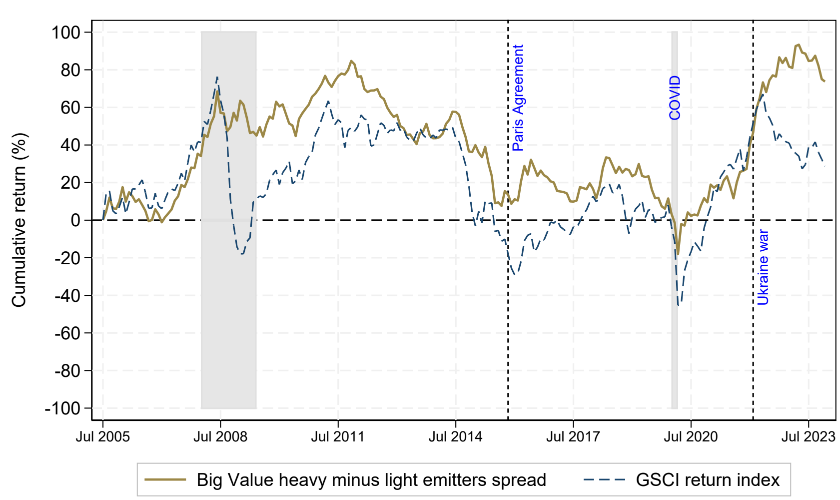
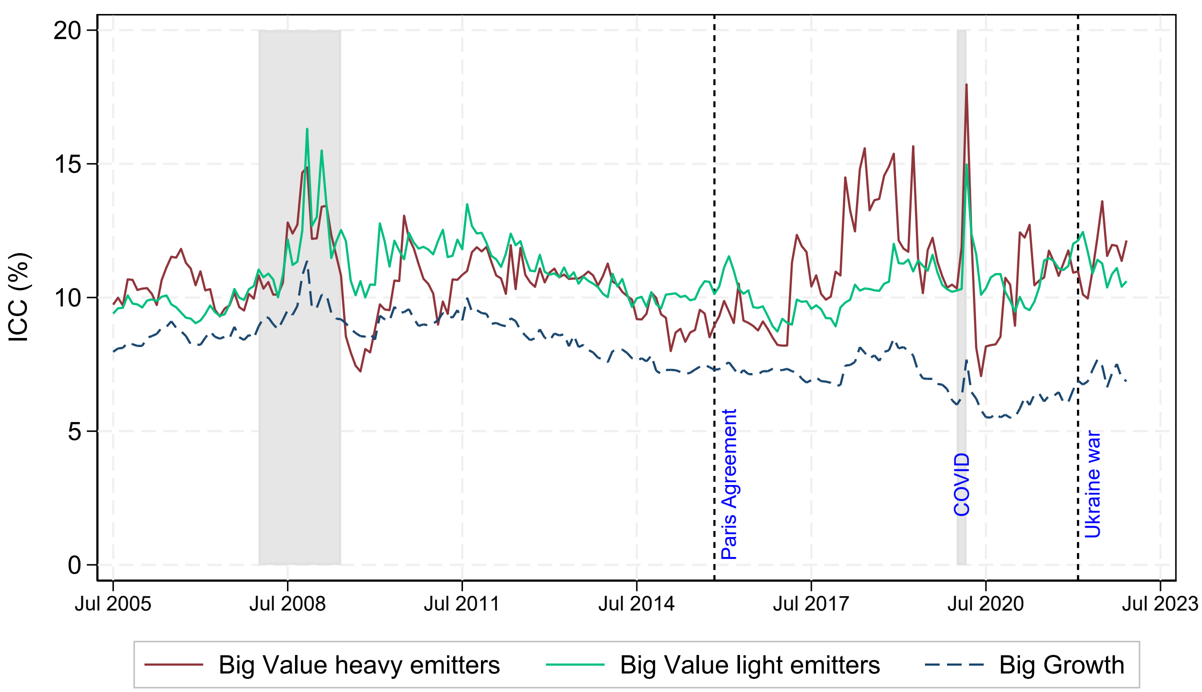


Figure 9: Implied costs of capital

This figure shows the ICCs of the two sub-portfolios that comprise Big Value portfolio: Big Value heavy emitters and Big Value light emitters. The Big Value portfolio is a long-only portfolio constructed following the method outlined on Ken French's website. Stocks are first sorted into two groups based on size (Small and Big) and then sorted into tertiles based on book-to-market equity. The Big Value portfolio consists of the big stocks in the highest book-to-market tertile. Big Growth portfolio consisting of stocks in the lowest book-to-market tertile is also plotted. Heavy emitters are defined as the top 10% most carbon-intensive firms in the CRSP sample (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. ICC is measured as the average of four ICC estimates using the methodologies of Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), following Mohanram and Gode (2013) and Eskildsen et al. (2024). Portfolio ICCs are computed as value-weighted averages of monthly ICCs of stocks within each portfolio. The shaded area denotes NBER recessions. The vertical dashed line denotes the Paris climate meeting in December 2015 and the start of the Ukraine war in February 2022. The sample period runs from July 2005 to December 2022 (in the years prior to 2016, we use backfilled emissions data to identify heavy emitters when no data is available).



Internet Appendix to

Dirty Business: Transition Risk of Factor Portfolios

(not for publication)

Abstract

This Internet Appendix presents supplementary material and results not included in the main body of the paper.

Table A.1: Heavy emitters share of Fama-French portfolios (number of firms)

This table presents share (in number of firms) of heavy emitters in Fama-French characteristic-sorted portfolios. See Table 2 for the full table description.

Panel A: SMB (Size)

	Portfolios						Difference	Factor
	Long					**Short**	**Long−Short**	
								SMB
	Small					Big		
2016	0.04	-	-	-	-	0.15	-0.11	-0.11
2017	0.04	-	-	-	-	0.14	-0.10	-0.10
2018	0.05	-	-	-	-	0.14	-0.09	-0.09
2019	0.05	-	-	-	-	0.14	-0.09	-0.09
2020	0.06	-	-	-	-	0.14	-0.08	-0.08
2021	0.06	-	-	-	-	0.13	-0.06	-0.06
2022	0.05	-	-	-	-	0.15	-0.10	-0.10
2023	0.05	-	-	-	-	0.15	-0.10	-0.10
mean	0.05	-	-	-	-	0.14	-0.09	-0.09
t-stat ($x = 0.10$)	(-19.90)	-	-	-	-	(16.38)	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-40.73)	(-40.73)
Backfilled emissions sample (2005–2023)								
mean	0.04	-	-	-	-	0.14	-0.10	-0.10
t-stat ($x = 0.10$)	(-18.02)	-	-	-	-	(18.52)	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-59.94)	(-59.94)

Table A.1: Heavy emitters share of Fama-French portfolios (number of firms)(continued)

Panel B: HML (Book-to-Market)

	Portfolios						Difference		Factor
	Long *Value*		**Neutral**		**Short** *Growth*		**Long−Short**		*HML*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.07	0.33	0.03	0.20	0.01	0.04	0.05	0.30	0.17
2017	0.06	0.30	0.04	0.17	0.03	0.05	0.03	0.25	0.14
2018	0.07	0.24	0.05	0.23	0.02	0.04	0.05	0.20	0.12
2019	0.08	0.17	0.05	0.26	0.02	0.04	0.07	0.13	0.10
2020	0.09	0.21	0.05	0.25	0.02	0.05	0.07	0.17	0.12
2021	0.09	0.23	0.06	0.21	0.03	0.04	0.06	0.19	0.13
2022	0.07	0.28	0.05	0.19	0.02	0.05	0.05	0.23	0.14
2023	0.05	0.20	0.05	0.22	0.03	0.07	0.02	0.13	0.08
mean	0.07	0.25	0.05	0.22	0.02	0.05	0.05	0.20	0.12
t-stat ($x = \bar{w}_v^k$)	(4.24)	(5.47)	(-0.57)	(7.06)	(-13.62)	(-24.94)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(7.93)	(9.70)	(12.23)
Backfilled emissions sample (2005–2023)									
mean	0.05	0.26	0.04	0.20	0.02	0.06	0.03	0.21	0.12
t-stat ($x = \bar{w}_v^k$)	(1.75)	(11.45)	(0.99)	(6.52)	(-13.09)	(-26.50)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(4.66)	(18.05)	(16.78)

Panel C: CMA (Investment)

	Portfolios						Difference		Factor
	Long *Conservative*		**Neutral**		**Short** *Aggressive*		**Long−Short**		*CMA*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.06	0.19	0.05	0.15	0.02	0.10	0.04	0.09	0.07
2017	0.06	0.18	0.04	0.13	0.04	0.12	0.02	0.06	0.04
2018	0.05	0.14	0.06	0.19	0.05	0.09	-0.00	0.06	0.03
2019	0.04	0.10	0.06	0.18	0.05	0.10	-0.01	-0.00	-0.01
2020	0.07	0.14	0.05	0.21	0.05	0.06	0.02	0.08	0.05
2021	0.10	0.23	0.08	0.17	0.02	0.04	0.08	0.19	0.13
2022	0.05	0.15	0.07	0.18	0.04	0.09	0.01	0.06	0.04
2023	0.02	0.08	0.07	0.18	0.07	0.14	-0.05	-0.07	-0.06
mean	0.06	0.15	0.06	0.17	0.04	0.09	0.01	0.06	0.04
t-stat ($x = \bar{w}_v^k$)	(0.93)	(0.73)	(1.58)	(4.39)	(-1.10)	(-4.06)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(1.04)	(2.32)	(1.88)
Backfilled emissions sample (2005–2023)									
mean	0.04	0.14	0.05	0.17	0.04	0.11	-0.00	0.03	0.02
t-stat ($x = \bar{w}_v^k$)	(-0.12)	(0.03)	(1.41)	(3.83)	(-0.09)	(-4.79)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(-0.06)	(2.49)	(1.64)

Table A.1: Heavy emitters share of Fama-French portfolios (number of firms) (continued)

Panel D: RMW (Operating Profitability)

	Portfolios						Difference		Factor
	Long *Robust*		**Neutral**		**Short** *Weak*		**Long−Short**		*RMW*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.06	0.09	0.04	0.12	0.04	0.28	0.02	-0.19	-0.08
2017	0.05	0.08	0.03	0.12	0.05	0.27	0.00	-0.19	-0.10
2018	0.10	0.09	0.06	0.18	0.04	0.16	0.06	-0.07	-0.00
2019	0.14	0.13	0.06	0.14	0.03	0.14	0.12	-0.01	0.05
2020	0.10	0.12	0.08	0.16	0.04	0.13	0.06	-0.00	0.03
2021	0.07	0.08	0.07	0.18	0.06	0.11	0.01	-0.03	-0.01
2022	0.13	0.15	0.06	0.16	0.03	0.09	0.09	0.06	0.08
2023	0.15	0.18	0.06	0.15	0.03	0.09	0.12	0.10	0.11
mean	0.10	0.12	0.06	0.15	0.04	0.16	0.06	-0.04	0.01
t-stat ($x = \bar{w}_v^k$)	(3.62)	(-1.81)	(1.35)	(1.55)	(-3.24)	(0.68)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(3.66)	(-1.13)	(0.35)
Backfilled emissions sample (2005–2023)									
mean	0.07	0.12	0.05	0.16	0.03	0.16	0.04	-0.05	-0.00
t-stat ($x = \bar{w}_v^k$)	(3.83)	(-4.76)	(1.73)	(2.44)	(-3.34)	(1.86)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(5.47)	(-3.09)	(-0.28)

Panel E: WML (Momentum)

	Portfolios						Difference		Factor
	Long *Winners*		**Neutral**		**Long** *Losers*		**Long−Short**		*WML*
	Small	Big	Small	Big	Small	Big	Small	Big	
2016	0.05	0.21	0.03	0.12	0.04	0.10	0.02	0.11	0.06
2017	0.03	0.10	0.04	0.15	0.06	0.23	-0.03	-0.13	-0.08
2018	0.05	0.09	0.06	0.17	0.05	0.14	-0.01	-0.05	-0.03
2019	0.04	0.09	0.04	0.14	0.07	0.22	-0.04	-0.14	-0.09
2020	0.04	0.09	0.05	0.14	0.07	0.26	-0.03	-0.18	-0.10
2021	0.08	0.15	0.06	0.12	0.04	0.14	0.05	0.02	0.03
2022	0.12	0.23	0.05	0.14	0.02	0.03	0.10	0.20	0.15
2023	0.05	0.12	0.07	0.18	0.04	0.13	0.01	-0.01	0.00
mean	0.06	0.13	0.05	0.14	0.05	0.16	0.01	-0.02	-0.01
t-stat ($x = \bar{w}_v^k$)	(0.76)	(-0.26)	(-0.16)	(0.51)	(-0.15)	(0.63)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(0.56)	(-0.49)	(-0.22)
Backfilled emissions sample (2005–2023)									
mean	0.04	0.13	0.04	0.15	0.04	0.16	0.00	-0.03	-0.01
t-stat ($x = \bar{w}_v^k$)	(0.68)	(-1.48)	(0.77)	(0.81)	(-0.17)	(0.93)	-	-	-
t-stat ($x = 0$)	-	-	-	-	-	-	(0.63)	(-1.22)	(-0.82)

Table A.2: Heavy emitters share of anomaly portfolios

This table presents market capitalization share of heavy emitters in characteristic-sorted anomaly portfolios from Chen and Zimmermann (2021). Detailed table description can be found in Table 3. The anomalies considered are: (i) cash holdings from Palazzo (2012); (ii) earnings consistency from Alwathainani (2009); (iii) cash-flow to price variance from Haugen and Baker (1996); (iv) EPS forecast dispersion from Diether et al. (2002); (v) pension funding status from Franzoni and Marin (2006); (vi) organizational capital from Eisfeldt and Papanikolaou (2013); and (vi) net debt to price from from Penman (2007). Exact definitions can be found in Chen and Zimmermann (2021).

Name	Citation	Sort	Sample	1	2	3	4	5	6	7	8	9	10	L−S
Heavy emitters in the short leg														
Cash to assets	Palazzo (2012)	Low to high	2016–2023	0.48	0.24	0.15	0.13	0.14	0.12	0.06	0.01	0.00	0.01	-0.47
				(14.53)	(6.18)	(0.80)	(0.15)	(0.77)	(0.05)	(-4.06)	(-45.89)	(-147.71)	(-27.36)	(-19.18)
			2005–2023	0.46	0.25	0.18	0.17	0.16	0.12	0.11	0.02	0.00	0.00	-0.45
				(15.87)	(5.93)	(1.40)	(1.54)	(1.23)	(-2.33)	(-1.78)	(-27.87)	(-175.48)	(-60.19)	(-22.39)
Earnings consistency	Alwathainani (2009)	Low to high	2016–2023	0.29	0.14	0.06	0.08	0.09	-	-	-	-	-	-0.20
				(3.05)	(2.67)	(-3.80)	(-1.19)	(-0.47)	-	-	-	-	-	(-2.81)
			2005–2023	0.20	0.13	0.11	0.14	0.10	-	-	-	-	-	-0.10
				(2.07)	(0.40)	(-1.23)	(0.66)	(-2.32)	-	-	-	-	-	(-2.46)
Cash-flow to price variance	Haugen & Baker (1996)	High to low	2016–2023	0.44	0.37	0.23	0.12	0.05	-	-	-	-	-	-0.39
				(13.96)	(5.33)	(8.63)	(-0.38)	(-16.24)	-	-	-	-	-	(-15.80)
			2005–2023	0.27	0.27	0.21	0.18	0.07	-	-	-	-	-	-0.21
				(3.72)	(4.32)	(8.20)	(2.39)	(-10.76)	-	-	-	-	-	(-5.28)
EPS forecast dispersion	Diether et al. (2002)	High to low	2016–2023	0.25	0.17	0.12	0.11	0.09	-	-	-	-	-	-0.16
				(2.61)	(2.30)	(0.20)	(-0.88)	(-3.51)	-	-	-	-	-	(-2.98)
			2005–2023	0.20	0.22	0.20	0.13	0.08	-	-	-	-	-	-0.12
				(2.29)	(3.64)	(2.68)	(-1.21)	(-9.70)	-	-	-	-	-	(-4.66)
R&D over market cap	Chan et al. (2001)	Low to high	2016–2023	0.16	0.03	0.02	0.04	0.28	-	-	-	-	-	0.12
				(5.09)	(-6.82)	(-8.30)	(-1.36)	(2.95)	-	-	-	-	-	(1.86)
			2005–2023	0.18	0.09	0.04	0.03	0.22	-	-	-	-	-	0.03
				(3.16)	(-0.05)	(-8.60)	(-6.17)	(3.37)	-	-	-	-	-	(0.70)
Pension funding status	Franzoni & Marin (2006)	Low to high	2016–2023	0.42	0.32	0.37	0.34	0.22	0.18	0.19	0.14	0.10	0.15	-0.26
				(6.67)	(3.29)	(3.00)	(2.69)	(0.57)	(-1.67)	(-0.58)	(-2.89)	(-5.91)	(-3.08)	(-5.99)
			2005–2023	0.39	0.38	0.34	0.33	0.24	0.23	0.17	0.12	0.11	0.14	-0.25
				(6.98)	(8.03)	(4.39)	(2.93)	(1.35)	(1.00)	(-2.10)	(-6.70)	(-10.10)	(-7.22)	(-10.22)
Organizational capital	Eisfeldt & Papanikolaou (2013)	Low to high	2016–2023	0.23	0.12	0.19	0.09	0.03	-	-	-	-	-	-0.20
				(3.64)	(-3.34)	(1.03)	(-4.51)	(-14.49)	-	-	-	-	-	(-7.74)
			2005–2023	0.18	0.17	0.20	0.22	0.06	-	-	-	-	-	-0.12
				(-0.63)	(-0.86)	(1.00)	(1.02)	(-4.22)	-	-	-	-	-	(-3.05)
Net debt to price	Penman et al. (2007)	High to low	2016–2023	0.46	0.33	0.36	0.30	0.02	-	-	-	-	-	-0.45
				(6.50)	(-0.45)	(0.33)	(-0.62)	(-56.11)	-	-	-	-	-	(-26.11)
			2005–2023	0.45	0.32	0.33	0.28	0.04	-	-	-	-	-	-0.41
				(6.53)	(-0.77)	(-0.09)	(-1.02)	(-11.19)	-	-	-	-	-	(-13.44)

Table A.3: Carbon intensity, absolute emissions, and E scores of book-to-market-sorted portfolios (equal weights)

This table presents equal-weighted portfolio carbon intensities, absolute Scope 1 emissions, and MSCI E scores for the Fama-French Big Value (BV) and Big Growth (BG) portfolios, and their differences. Fama-French portfolios are defined in Table 2. Each Fama-French portfolio is further separated into heavy and light emitter portfolios. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. For the purpose of categorization carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue (measured in $mtCO_2e/\$M$). Scope 1 measures only direct emissions from production. Scope 2 measures direct emissions from consumption of purchased electricity, heat, or steam. Upstream Scope 3 measures emissions not produced by the company itself, but that are part of its value chain. The different emission measures are: Scope 1 carbon intensity, Scope 1 and 2 carbon intensity, Scope 1, 2, and upstream Scope 3 carbon intensity, absolute Scope 1 emissions (measured in $MmtCO_2e$), and standardized MSCI E scores, where a lower score indicates a worse score (more polluting). t-statistics for the test of the mean being different from zero are reported. The data are annual and the main sample period is from 2016 to 2023.

					Difference	
Measure	Sample	Big Value heavy	Big Value light	Big Growth light	BV heavy − BV light	BV light − BG light
Carbon intensity (Scope 1)	2016–2023	5.142	0.109	0.149	5.033	-0.040
		-	-	-	(7.535)	(-3.693)
	2005–2023	7.327	0.170	0.200	7.157	-0.030
		-	-	-	(9.551)	(-3.852)
Carbon intensity (Scope 1 + 2)	2016–2023	6.054	0.259	0.357	5.795	-0.097
		-	-	-	(8.232)	(-3.781)
	2005–2023	8.273	0.342	0.451	7.931	-0.109
		-	-	-	(10.768)	(-9.383)
Carbon intensity (Scope 1, 2, + 3)	2016–2023	8.570	1.151	1.638	7.419	-0.487
		-	-	-	(10.442)	(-7.002)
	2005–2023	10.554	1.501	1.913	9.053	-0.412
		-	-	-	(14.864)	(-6.486)
Absolute Scope 1 emissions	2016–2023	8.600	0.132	0.174	8.468	-0.042
		-	-	-	(5.886)	(-1.971)
	2005–2023	8.692	0.263	0.193	8.429	0.070
		-	-	-	(11.533)	(1.559)
MSCI E scores	2016–2023	-1.640	0.330	0.251	-1.969	0.079
		-	-	-	(-20.282)	(1.100)
	2012–2023	-1.567	0.348	0.241	-1.915	0.107
		-	-	-	(-31.270)	(2.110)

Table A.4: Big Value realized returns and implied cost of capital (equal-weighted)

This table presents linear regressions of equal-weighted portfolio return differences and ICC differences on time period dummies. Post Paris is a dummy variable equal to one after December 2015 (Paris climate meeting) and zero otherwise. Post 2021 is a dummy variable equal to one during the high-inflation years of 2021 and 2022, and zero otherwise. Panel A reports the results for the realized returns, and Panel B reports the results for the ICCs. In both panels, columns (1)-(3) present the results for the difference between the Big Value heavy emitters and Big Value light emitters portfolios, while columns (4)-(6) present the results for the difference between the Big Value light emitters and Big Growth light emitters portfolios. Fama-French portfolios are defined in Table 2. Each Fama-French portfolio is further separated into heavy and light emitter portfolios. Heavy emitters are defined as the top 10% of the most carbon-intensive firms in the CRSP sample each year (with the five least carbon-intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utilities firms are excluded when constructing the portfolios. ICC is measured as the average of four ICC estimates using the methodologies of Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005), following Mohanram and Gode (2013) and Eskildsen et al. (2024). Portfolio ICCs are computed as value-weighted (equal-weighted) averages of monthly ICCs of stocks within each portfolio. All returns are annualized and are in %. t-statistics based on Newey and West (1987) standard errors are reported in parentheses (the lag length is selected automatically using the Newey and West (1994) procedure). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively. The return series are monthly, and the sample period runs from July 2005 to December 2023, with the ICC series ending in December 2022.

Panel A: Returns

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	4.90	1.25	1.25	−1.31	−0.34	−0.34
	(1.00)	(0.19)	(0.23)	(−0.46)	(−0.09)	(−0.11)
Post 2016		8.43	0.74		−2.24	−8.84
		(0.85)	(0.08)		(−0.39)	(−1.63)
Post 2021			30.75**			26.38***
			(2.01)			(2.79)
Observations	222	222	222	222	222	222

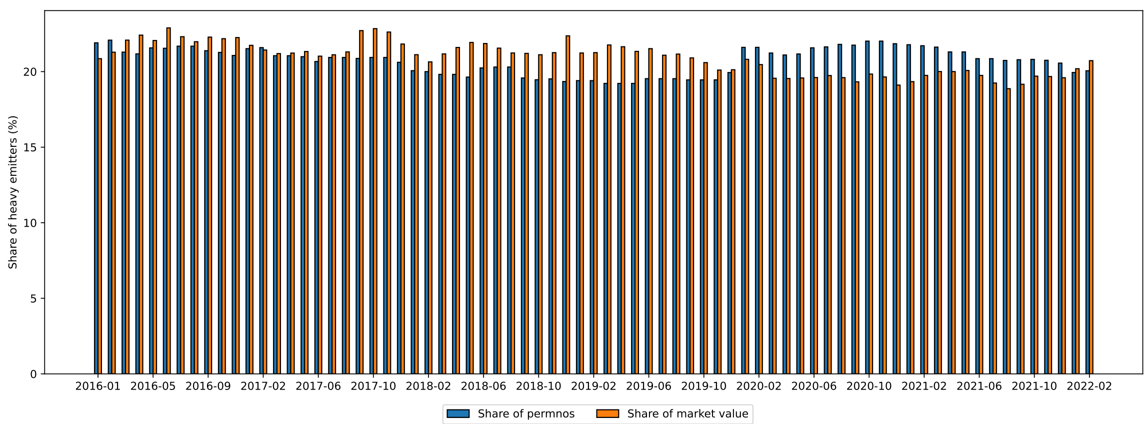
Panel B: ICC

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.29	0.13	0.13	2.56***	1.87***	1.87***
	(1.28)	(0.48)	(0.48)	(6.98)	(6.01)	(6.67)
Post Paris		0.39	0.24		1.71***	1.46***
		(0.89)	(0.50)		(3.54)	(3.02)
Post 2021			0.51			0.90
			(0.70)			(1.29)
Observations	210	210	210	210	210	210

Figure A.1: Heavy emitter share in Vanguard's value and growth ETFs

This figure shows share of heavy emitters in the holdings of Vanguard's value and growth ETFs. Panel (a) displays the holdings of the Vanguard Value Index Fund ETF (VTV), and Panel (b) displays the holdings of the Vanguard Growth Index Fund ETF (VUG). Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers). Holdings data are sourced from 13-F filings. The data are quarterly and the sample period is from 2016 to 2022.

(a) Vanguard Value Index Fund ETF (VTV)



(b) Vanguard Growth Index Fund ETF (VUG)

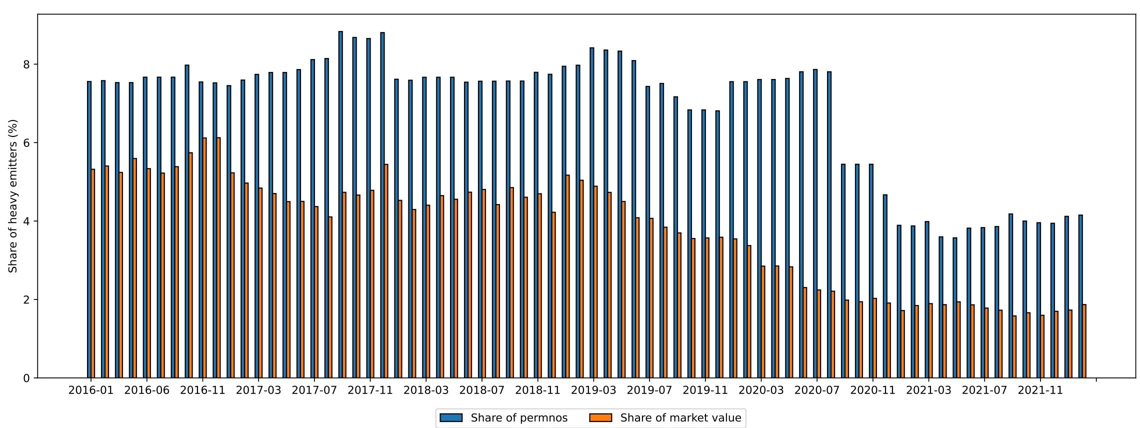
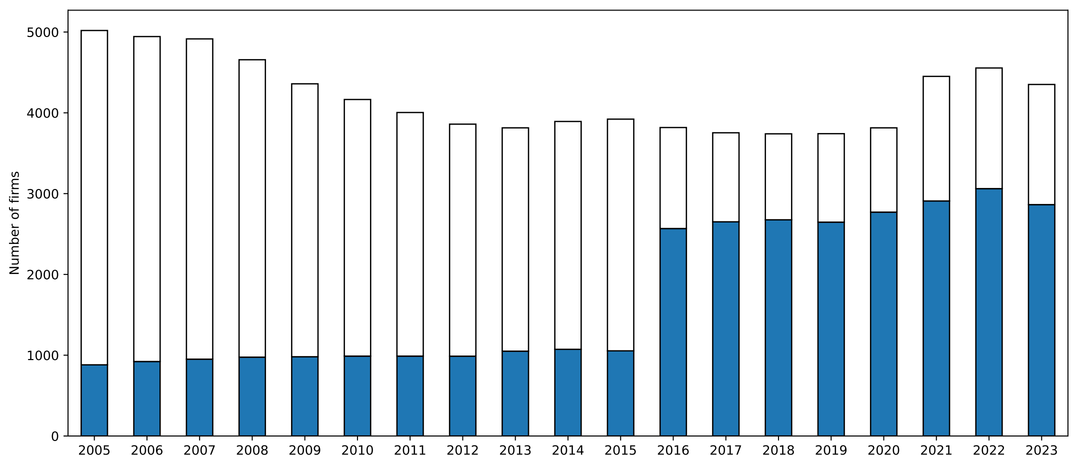


Figure A.2: Greenhouse gas emissions data coverage

This figure shows the coverage of the firm-level GHG emissions data. Panel (a) shows the number of firms for which emissions data are available relative to the full universe of the publicly-listed US firms (CRSP sample). Panel (b) shows the total market capitalization of the firms for which emissions data are available relative to the total market capitalization of the full CRSP universe. Market capitalization is in trillion $. The data are annual and the sample period is from 2005 to 2023.

(a) Number of firms



(b) Market capitalization

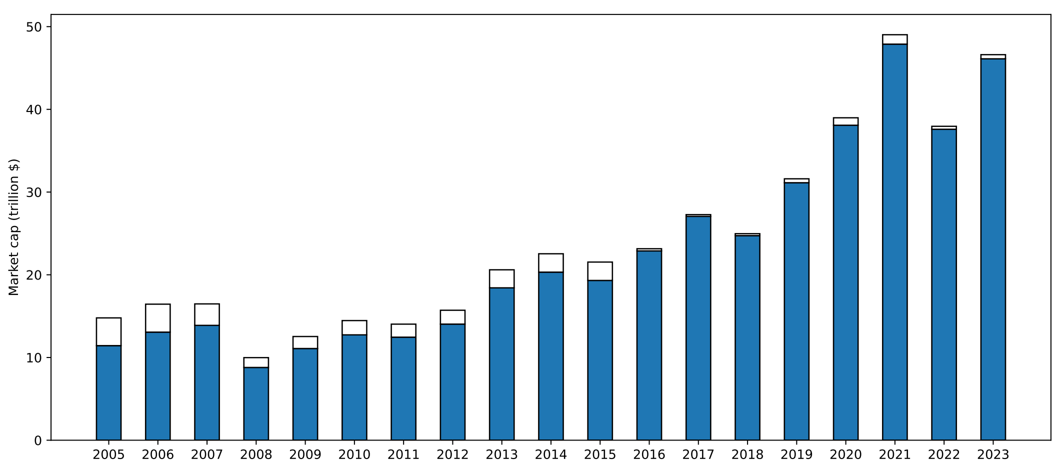
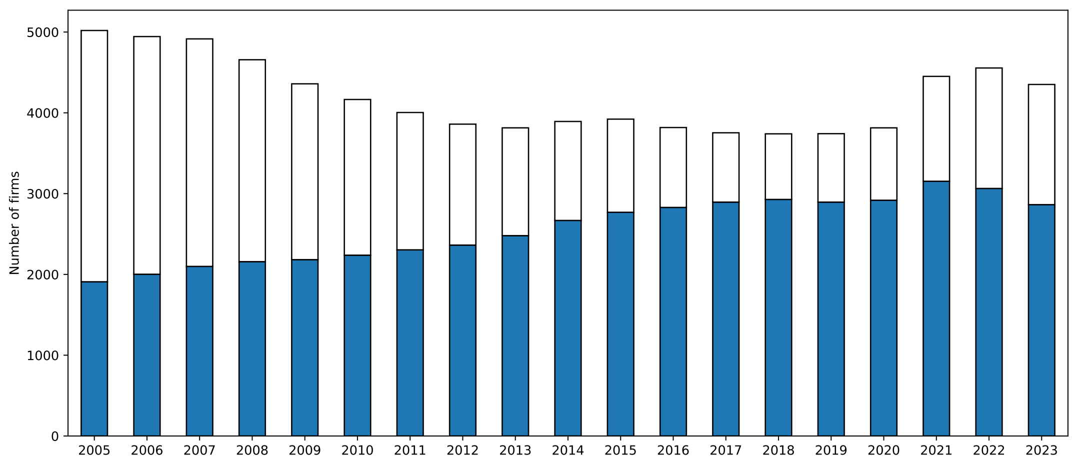


Figure A.3: Greenhouse gas emissions data coverage (back-filled data)

This figure shows the coverage of the firm-level GHG emissions data. Panel (a) shows the number of firms for which emissions data are available relative to the full universe of the publicly-listed US firms. Panel (b) shows the total market capitalization of the firms for which emissions data are available relative to the total market capitalization of the full CRSP universe. Market capitalization is in trillion $. The data are annual and the sample period is from 2005 to 2023.

(a) Number of firms



(b) Market capitalization

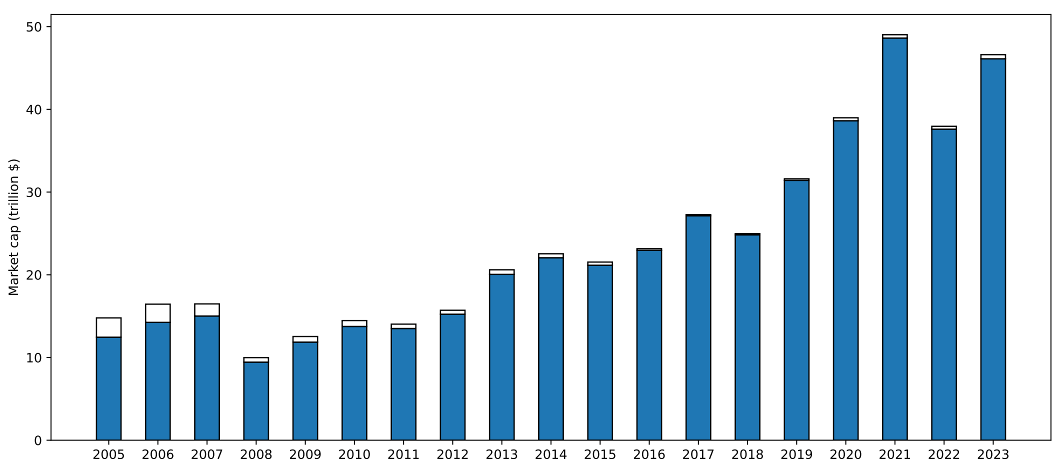
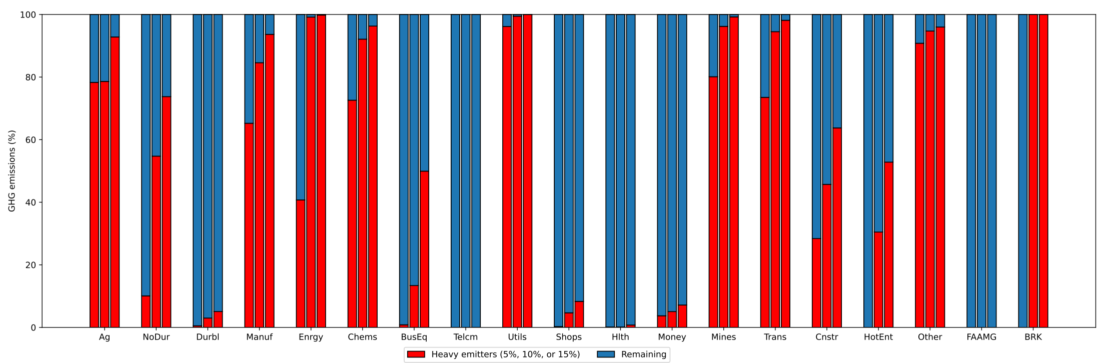


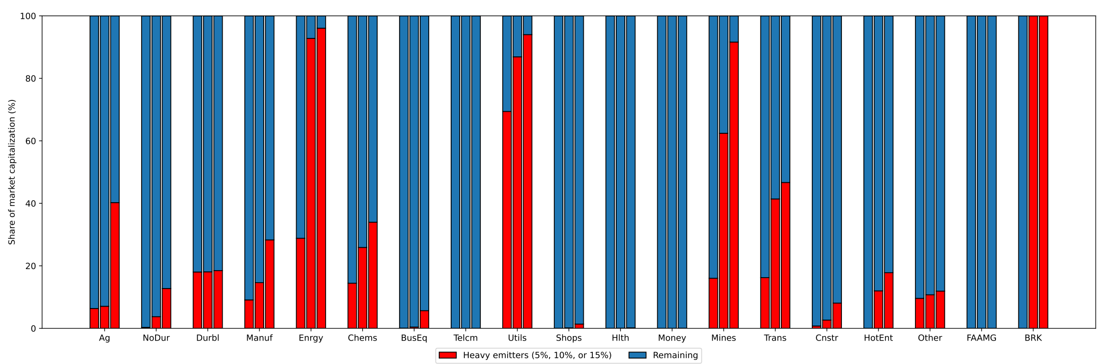
Figure A.4: Emissions and market capitalization of heavy emitters (share of total)

This figure shows the share of the total (a) GHG emissions, (b) market capitalization, and (3) number of firms corresponding to the top 5%, top 10%, and top 15% of firms sorted on carbon intensity. Carbon intensity is defined as the sum of Scope 1 and Scope 2 emissions divided by the firm's total revenue (measured in mtCO_2e/\$M). Industry categories are explained in Figure 1. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

(a) Emissions



(b) Market capitalization



(c) Number of firms

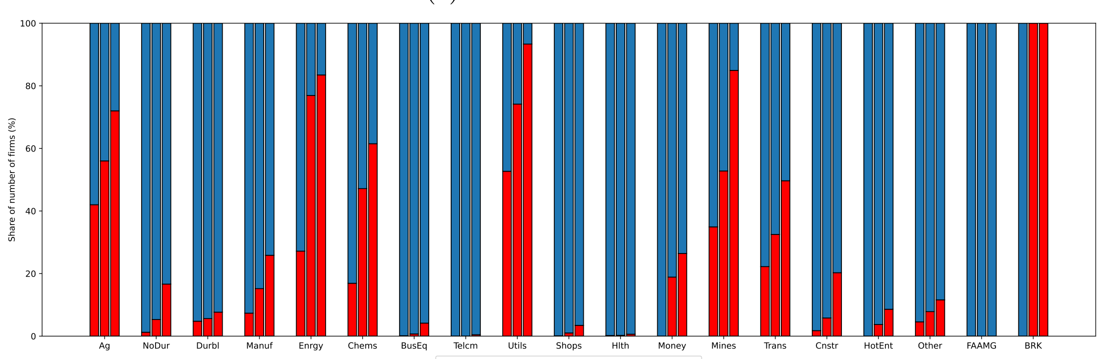
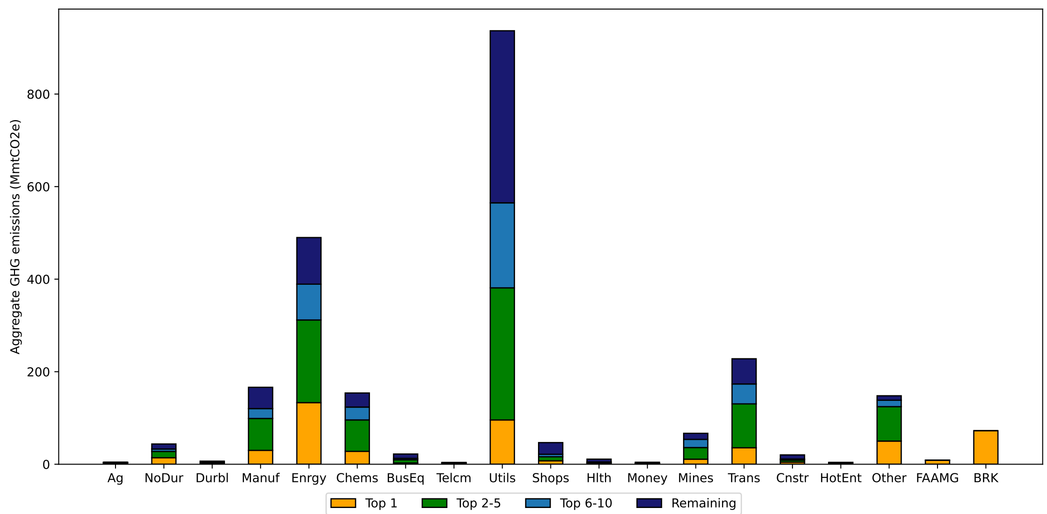


Figure A.5: Distribution of aggregate GHG emissions and market capitalization by industry

Panel (a) of this figure shows the total Scope 1 GHG emissions among publicly-traded US firms by industry (measured in million mtCO_2e). Scope 1 measures only direct emissions from production. Panel (b) shows the total market capitalization (in trillion \$) and total number of firms across each industry. In each figure, the contributions of the top firms (either by aggregate emissions or market capitalization) are indicated. Industry categories are explained in Figure 1. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

(a) Aggregate emissions



(b) Market capitalization

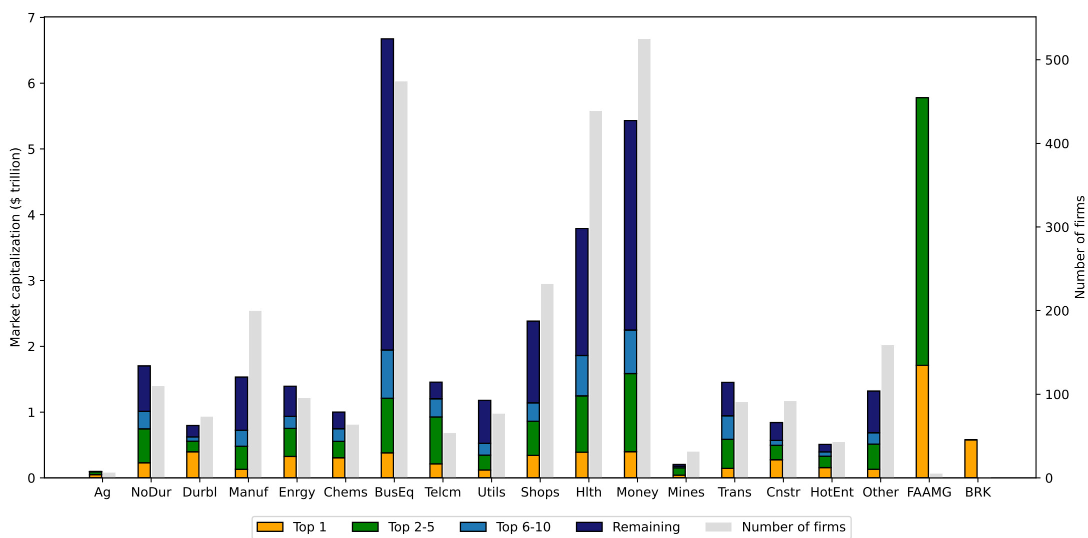
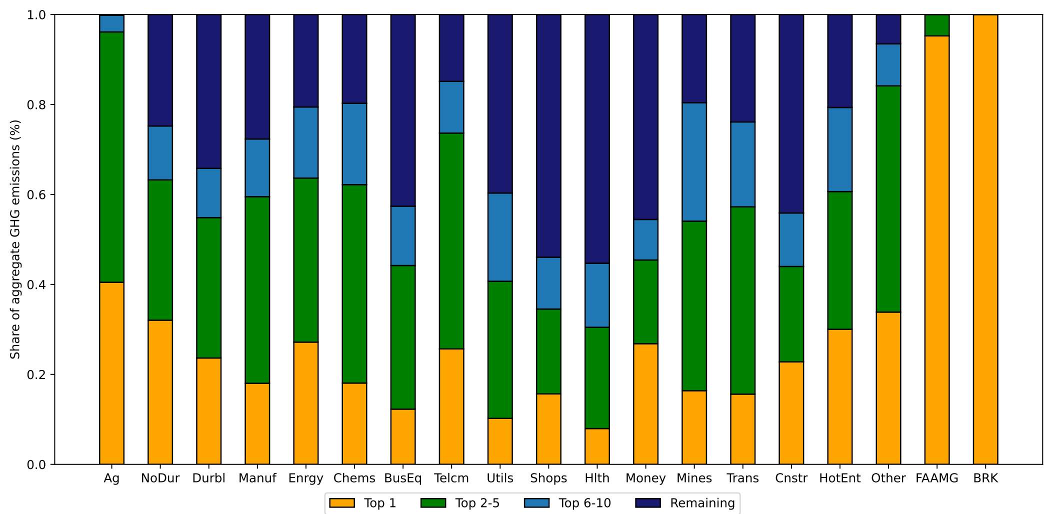


Figure A.6: Aggregate emissions and market capitalization by industry (share of total)

Panel (a) of this figure shows the relative share of top firms of the total GHG emissions among publicly-traded US firms in each industry. Total GHG emissions are defined as Scope 1 emissions. Scope 1 measures only direct emissions from production. Panel (b) shows the relative share of total market capitalization in each industry. Industry categories are explained in Figure 1. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

(a) Aggregate emissions



(b) Market capitalization

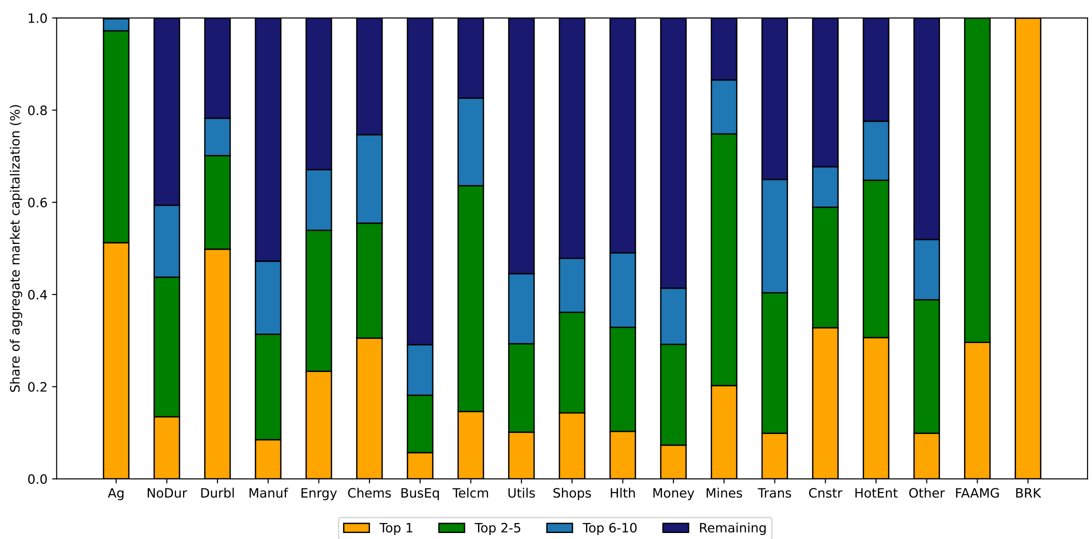


Figure A.7: Contribution to aggregate emissions (double sort)

This shows the percentage of total GHG emissions from US public firms accounted for by the heaviest emitters (in absolute GHG emissions) of the top 10% of the most carbon intensive firms. Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue. Scope 1 measures only direct emissions from production. Firms are fist ranked by their carbon intensities each year, and then only the top 10% of most carbon-intensive firms are considered. Next, this set of firms is ranked on absolute GHG emissions from highest to lowest. The plot shows the cumulative fraction of the aggregate GHG pollution of the ranked firms. The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

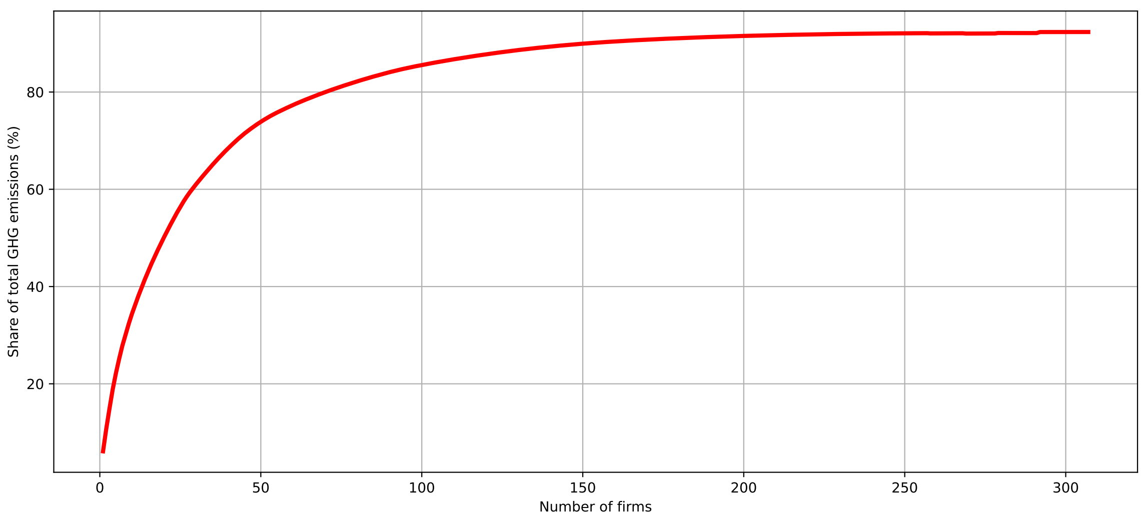


Figure A.8: Intersection of heavy emitters and firms covered by TPI Centre

This figure shows the industry distribution of firms covered by the LSE Transition Pathway Initiative (TPI) Centre. For each industry, the figure indicates how many firms that were ever covered by TPI Centre are classified as heavy emitters. Heavy emitters are defined as the top 10% of the most carbon intensive firms in the CRSP sample each year (with the four least carbon intensive firms substituted for the four firms producing vehicles with internal combustion engines). Carbon intensity is defined as Scope 1 emissions divided by the firm's total revenue. Scope 1 measures only direct emissions from production. The data are annual and the sample period is from 2016 to 2023

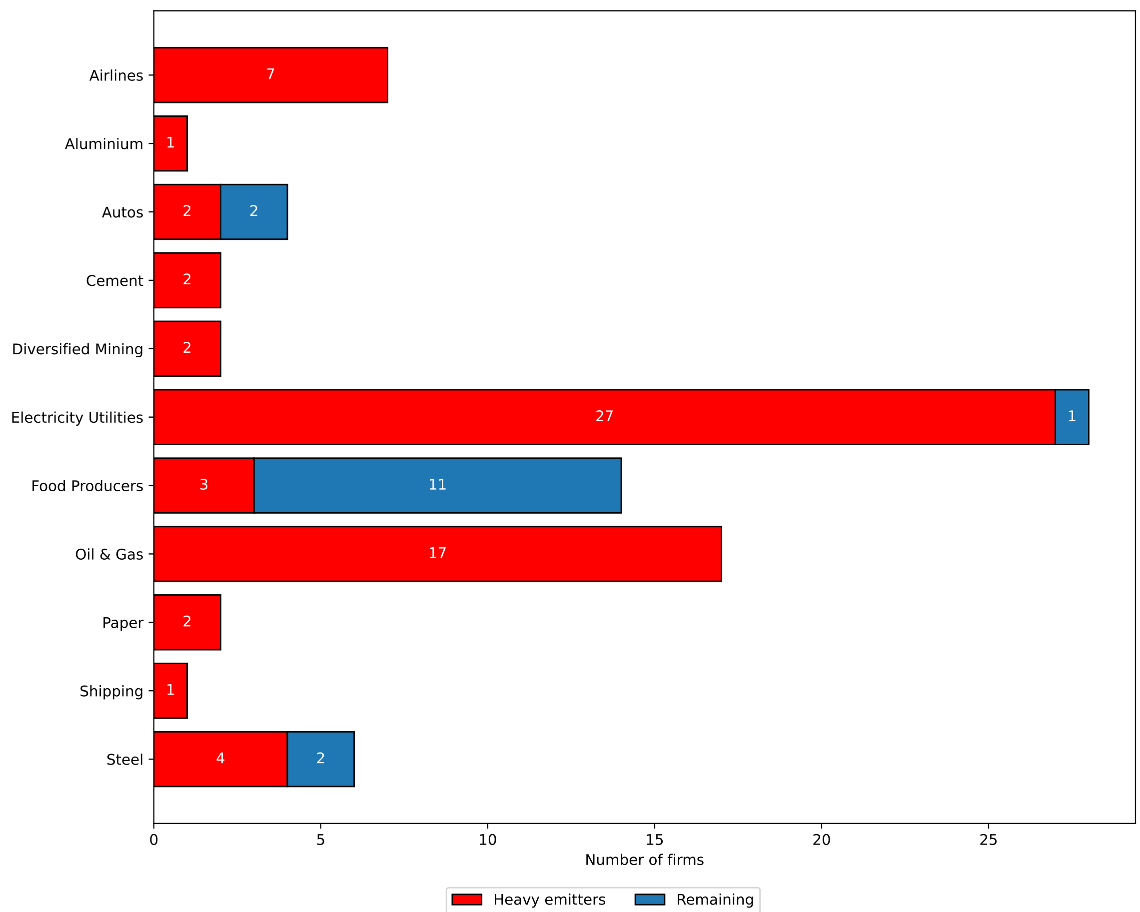


Figure A.9: Aggregate GHG emissions

This figure shows the aggregate Scope 1 GHG emissions among publicly-traded US firms over time. GHG emissions are expressed in million metric tons of carbon dioxide equivalent ($MmtCO_2e$). Scope 1 measures only direct emissions from production.

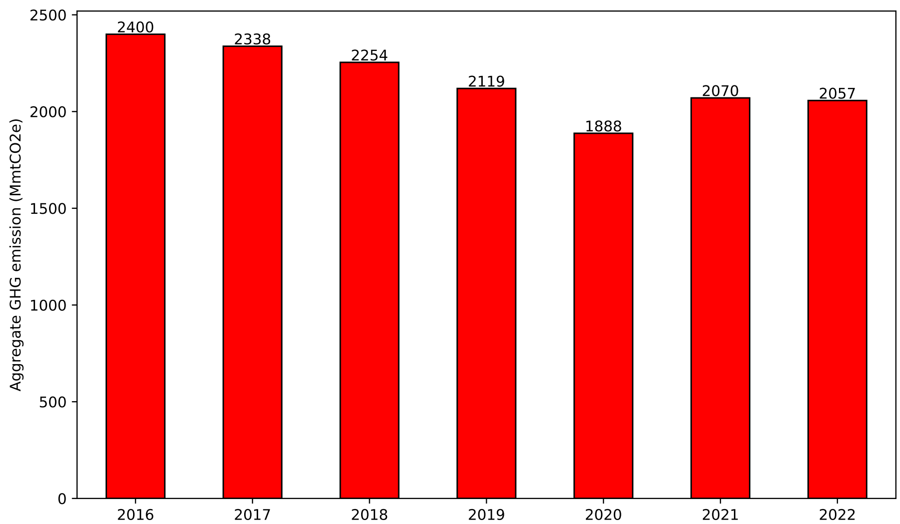
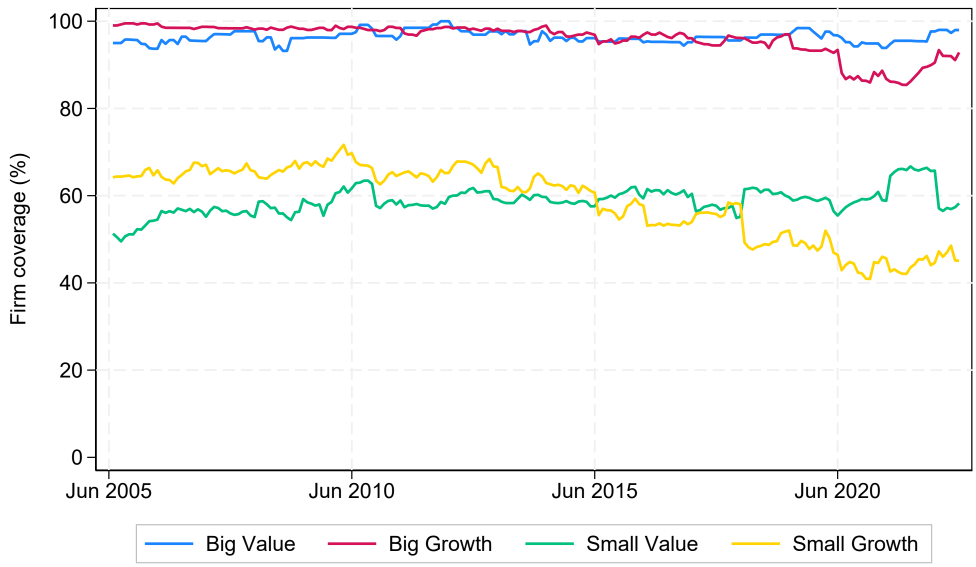


Figure A.10: ICC Coverage

This figure shows the coverage of the implied cost of capital (ICC) data as a percentage of (a) the number of firms and (b) the total market capitalization of the firms in the four Fama-French portfolios sorted on size and book-to-market (Big Value, Big Growth, Small Value, and Small Growth). We use for each firm the equal-weighted average of four ICC measures: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). The sample period runs from July 2005 to December 2022.

(a) Firm coverage



(b) Market capitalization coverage

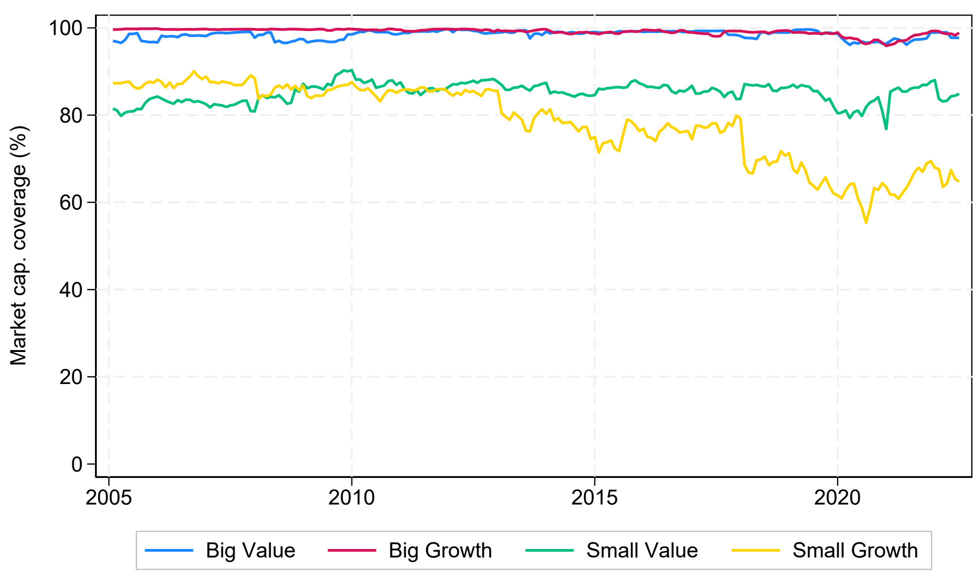


Figure A.11: Returns of heavy and light emitters of the Big Value portfolio (equal-weighted)

This figure shows the cumulative equal-weighted returns of the two sub-portfolios that comprise the Big Value portfolio: Big Value heavy emitters and Big Value light emitters. The Big Value portfolio is a long-only portfolio constructed following the method outlined on Ken French's website. Stocks are first sorted into two groups based on size (Small and Big) and then into tertiles based on book-to-market equity. The Big Value portfolio consists of the big stocks in the highest book-to-market tertile. The Big Growth portfolio, consisting of stocks in the lowest book-to-market tertile, is also plotted. Heavy emitters are defined as the top 10% most carbon-intensive firms in the CRSP sample (with the five least carbon-intensive firms substituted for the five firms producing vehicles with internal combustion engines), while light emitters are firms that do not fall into this category. The shaded area denotes NBER recessions. The vertical dashed lines denote the Paris climate meeting in December 2015 and the start of the Ukraine war in February 2022. The return series are monthly, and the sample period runs from July 2005 to December 2023 (in the years prior to 2016, backfilled emissions data are used to identify heavy emitters when no data is available).

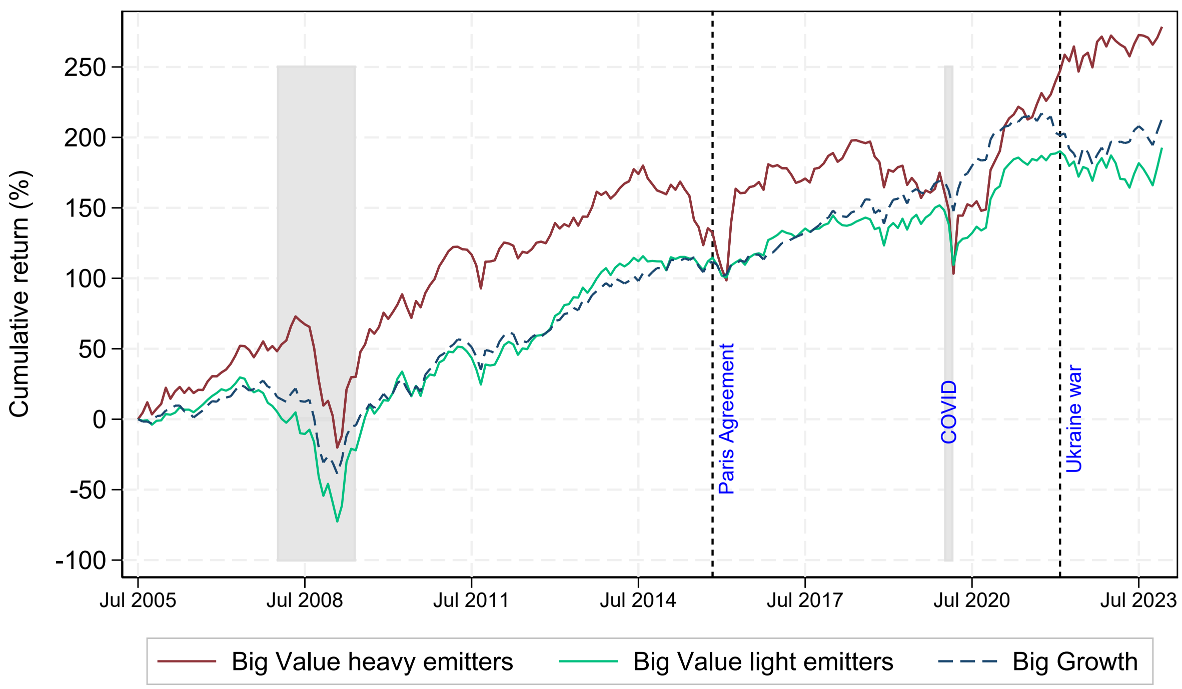


Figure A.12: Implied costs of capital (equal-weighted)

This figure shows the ICCs of the two sub-portfolios that comprise Big Value portfolio: Big Value heavy emitters and Big Value light emitters. The Big Value portfolio is a long-only portfolio constructed following the method outlined on Ken French's website. Stocks are first sorted into two groups based on size (Small and Big) and then sorted into tertiles based on book-to-market equity. The Big Value portfolio consists of the big stocks in the highest book-to-market tertile. Big Growth portfolio consisting of stocks in the lowest book-to-market tertile is also plotted. Heavy emitters are defined as the top 10% most carbon-intensive firms in the CRSP sample (with the five least carbon intensive firms substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. ICC is measured as the average of four ICC estimates using the methodologies of Claus and Thomas (2001), Gebhardt et al. (2001), Easton (2004), Ohlson and Juettner-Nauroth (2005), following Mohanram and Gode (2013) and Eskildsen et al. (2024). Portfolio ICCs are computed as equal-weighted averages of monthly ICCs of stocks within each portfolio. The shaded area denotes NBER recessions. The vertical dashed line denotes the Paris climate meeting in December 2015 and the start of the Ukraine war in February 2022. The sample period runs from July 2005 to December 2022 (in the years prior to 2016, we use backfilled emissions data to identify heavy emitters when no data is available).