Dirty Business: Transition Risk of Factor Portfolios

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Abstract

The top 10% of carbon-intensive firms account for over 90% of Scope 1 emissions from U.S. public companies. Exposure to these heavy emitters varies across factor portfolios, reaching 35% of Value portfolios but only 5% of Growth portfolios. Focusing on the heavy and light emitters within the Big Value portfolio (stocks with similar fundamentals, but different 'brownness'), we find that after the Paris Agreement until the COVID period, heavy emitters underperformed and saw an increase in their expected return proxies. The expected return proxies for these sub-portfolios have converged since, suggesting no persistent incremental premium for transition risk – a pattern that is only visible when we do not compare firms across the value-growth spectrum. Moreover, comparing Big Value and Big Growth light-emitter portfolios (stocks with similar 'greenness', but different fundamentals), we find that Big Growth light emitters outperformed and exhibited declining expected return proxies, suggesting that climate concerns alone cannot explain the recent disappearance of the Value premium.

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1 Introduction

Among U.S. publicly listed firms, both carbon intensity and absolute emissions are highly skewed. A small subset of companies accounts for the vast majority of pollution, while the remainder exhibit broadly similar and relatively low emission levels. We document that just 10% of firms (roughly 300 names) are responsible for over 90% of total Scope 1 greenhouse gas emissions. If the global economy transitions toward a low-emissions future, whether through technological innovation, regulatory tightening, or shifting investor and consumer preferences, these 'heavy emitters' (i.e., 'brown' firms) could face heightened uncertainty and an elevated risk of substantial devaluation.[1] Investors holding these firms in their portfolios would then be exposed to carbon transition risk. In this paper, we focus on the heavy emitters.[2] We begin by examining how these firms are distributed across investment portfolios, and then assess whether they are associated with any incremental return premium.

We focus on a select set of widely used portfolios. This choice is consistent with the Arbitrage Pricing Theory of Ross (1976), which implies that a small number of factors span the cross-section of returns, and with the well-documented prominence of style and factor investing in practice (see, e.g., Barberis and Shleifer, 2003; Froot and Teo, 2008). Style and factor investing involves sorting stocks into portfolios based on some observable firm characteristics that are believed to be related to future stock returns. Some of these characteristics may be associated with carbon emissions and, consequently, carbon transition risk exposures, potentially in a non-linear manner. Among investment styles, Value and Growth are perhaps the most well-known and widely used, typically subdivided into Big Value/Growth and Small Value/Growth styles. For example, Morningstar, a key ratings provider, classifies U.S. equity mutual funds based mostly on size and value-growth characteristics (see Morningstar, 2020; Cohen, Kim, and So, 2024). Therefore, we focus on the Value and Growth styles before extending the analysis to other factor portfolios.

We begin by identifying who the heavy emitters are. Using a full sample of CRSP firms

[1] For instance, Cheng, Jondeau, Mojon, and Vayanos (2024), studying the effect of green investors on stock prices in a dynamic equilibrium asset-pricing model, find large drops in the stock prices of the 'brownest' firms and only moderate increases for greener firms. Similarly, Barnett (2024) shows, in a general equilibrium model, that climate-change-related expectations of fossil fuel restrictions lead to unambiguous decreases in the prices of such firms. The U.S. coal industry's experience serves as a tangible example of how technological change, regulation, and investor pressure can converge, leading to industry-wide adverse impacts (see, e.g., Bassen, Kaspereit, and Buchholz, 2021; Scott, 2020; Jagannathan, Ravikumar, and Sammon, 2018).

[2] We deliberately concentrate on the extreme brown tail of the distribution, where firm classification is largely unambiguous, in contrast to many existing studies that attempt to classify 'green' firms, despite the ambiguity around what qualifies as 'green' (see, e.g., Cohen, Gurun, and Nguyen, 2020; Cheema-Fox, Serafeim, and Wang, 2023; Klausmann, Krueger, and Matos, 2024, for a discussion about 'green' classification).

from 2016 to 2023, matched 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. Together, the Scope 1 emissions of the firms in our sample represent approximately a third of total annual U.S. emissions, i.e, a meaningful share in economic terms.[3] Each year, we sort our sample firms by carbon intensity (greenhouse gas emissions scaled by revenue). As mentioned earlier, 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. Notably, we find that just 10% of the most carbon-intensive firms are, on average, responsible for 92% of the aggregate absolute Scope 1 emissions of U.S. public firms, and 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. Moreover, the top 10% of firms ranked by carbon intensity overlap, on average, 70% with those ranked by absolute Scope 1 emissions, and their total emissions account for 96% of the emissions from the top 10% of absolute emitters. Thus, when focusing on the upper tail, the distinction between intensity and absolute emissions is largely immaterial, hence our analysis sidesteps the ongoing debate on this issue (see, e.g., Bolton and Kacperczyk, 2021; Aswani, Raghunandan, and Rajgopal, 2024; Kacperczyk, 2026).[4] Additionally, emissions data for heavy emitters are predominantly reported (about 90% among large firms) rather than estimated by the data provider, which alleviates the concerns raised by Aswani et al. (2024) that vendor-estimated emissions may distort empirical inferences.[5]

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.[6] We validate our classification of heavy emitters

[3]We discuss comparisons to aggregate emissions in the Internet Appendix.

[4]Our list of the most salient heavy emitters is also 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).

[5]We follow the primary classification in Aswani et al. (2024) and identify emissions observations as estimated when the Trucost variable "Scope 1 Carbon Disclosure" contains the term 'estimate.' Large firms are defined as those belonging to the Fama–French Big portfolio.

[6]The exact cutoff of 10% is immaterial to our main conclusions, as similar results are observed with different cutoffs. 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. One 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. To address this concern, we include five manufacturers

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 97% probability that it will remain in that category the following year. Given the strong persistence of heavy emitters and our use of emissions data solely to identify the upper tail of the distribution, the econometric specification issues raised by Zhang (2025) regarding the timing of emissions measurement are less of a concern for our approach.[7] Second, we confirm our classification by cross-referencing it with environmental (E) scores from MSCI, finding high correlations: the heavy emitters have the lowest (worst) 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 Transition Pathway Initiative Centre, finding that our classification aligns closely with theirs.

Having established our list of heavy emitters, we explore the types of portfolios in which heavy emitters typically fall. Pástor, Stambaugh, and Taylor (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 the 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.

Examining the market capitalization share of heavy emitters in Fama-French portfolios, we observe the starkest patterns among the book-to-market-sorted portfolios. Specifically, heavy emitters represent, on average, 37% of the value of the Big Value portfolio and only 3% of the Big Growth portfolio, with this difference being highly statistically significant and consistent over time. These patterns also hold when examining simple firm counts rather than market capitalization shares. By construction, our set of heavy emitters comprises 10% of the sample of firms (12% in terms of market capitalization). Hence, if there were no relationship between being a heavy emitter and the characteristic on which the portfolios are sorted, we would expect to see an average share of around 10% of firms in each portfolio. Instead the market cap share of heavy emitters in the Big Value and Big Growth portfolios is almost three times bigger and over three times smaller, respectively, than would be expected.

of internal combustion engines and vehicles in our set of heavy emitters, replacing the five least carbon-intensive firms within the top 10% of carbon-intensive firms. However, including or excluding them does not materially affect our main results.

[7] For our return analysis, we construct portfolios using lagged emissions data to identify heavy emitters, however those results are not sensitive to the exact timing of emissions measurement.

Notably, our results also show that not all of the Value portfolio is comprised of brown firms and the majority of the Value portfolio is in fact quite green, a key fact that we exploit in our methodology in analyzing whether there is a persistent premium for transition risk.

We also analyze 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 portfolios related to Fama-French factor themes to reinforce our findings above. Analyzing more than a dozen value strategies, including those based on intangible returns, cash productivity, enterprise multiples, sales-to-price, earnings-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). As additional validation, we examine 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 stable over time.[8] Hence, we find that value investing (regardless of how 'value' is defined) is associated with significant heavy emitter exposure, whereas Growth investing largely avoids such exposure.[9]

The substantial and persistent presence of heavy emitters in value strategy portfolios provides a natural setting to address the open question of whether investors are differentially compensated for holding brown firms, at least within the value segment.[10] Focusing specifically on the Big Value portfolio is motivated by several considerations. First, as noted earlier, value investing remains a cornerstone of style- and factor-based strategies. Second, if the goal is to reduce total global emissions, as emphasized by Bolton and Kacperczyk (2021) and others, then value portfolios are of particular interest: the firms in the Fama-French Big Value portfolio emit roughly three times more than those in the Big Growth portfolio, despite having only about one-fifth of its total market capitalization.[11] Third, value firms

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

[9] For other strategies, like those based on firm investment, the prevalence of heavy emitters often shifts between portfolios, driven by the cyclicality of many heavy-emitting firms' capital expenditures and commodity price fluctuations. We focus primarily on the book-to-market sorted portfolios, deferring the discussion of other portfolios (e.g., investment- and profitability-sorted portfolios) to later sections to facilitate flow.

[10] While some theory suggests that investors should be compensated for transition risk (see, e.g., Heinkel, Kraus, and Zechner, 2001; Pástor, Stambaugh, and Taylor, 2021), there is no consensus in the empirical literature on whether they are compensated or what the appropriate level of compensation should be. See, for example, Bolton and Kacperczyk (2021); Giglio, Maggiori, Rao, Stroebel, and Weber (2021b); Pástor et al. (2022); Bolton and Kacperczyk (2023); Sautner, Van Lent, Vilkov, and Zhang (2023b); Aswani et al. (2024); Zhang (2025); Bolton and Kacperczyk (2024), and the literature reviews in Giglio, Kelly, and Stroebel (2021a); Eskildsen, Ibert, Jensen, and Pedersen (2026).

[11] The Internet Appendix reports total emissions and size across the Big Value and Big Growth portfolios.

are distinct in ways that make direct comparisons across the value–growth spectrum potentially misleading. For example, the heavy emitter Chevron, with an average book-to-market (B/M) ratio of 0.71 during our sample period and a dividend yield exceeding 4%, is a typical value firm, while the light emitter Tesla, with a B/M ratio below 0.10 and no dividend, is a canonical growth stock and a permanent member of the Big Growth portfolio. More generally, the average book-to-market ratio of Big Value stocks is nearly six times higher than that of Big Growth stocks.[12] Comparing firms across this spectrum is unlikely to precisely reveal whether transition risk is priced, as they differ on numerous dimensions beyond emissions that could be difficult to control for. To address this, we focus on comparisons within the value portfolio, isolating firms that are similar in key fundamentals (e.g., size, B/M ratio) but differ in emissions exposure.[13] Specifically, we examine 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 analyze their realized and expected returns. Fourth, our setting offers near-complete coverage of both emissions data and expected return proxies (implied cost of capital and option-implied lower bounds) for Big Value constituents, whereas coverage is limited among smaller-cap firms. Finally, a key observation is that, across a broad set of measures, the Big Value and Big Growth light-emitter portfolios do not meaningfully differ in their level of 'greenness.' In other words, the Value light-emitter portfolio is just as green as its Growth counterpart.

Our objective is to examine whether Big Value heavy emitters earn an incremental premium relative to their light-emitting counterparts within the Value universe.[14] Inference

[12] The Internet Appendix plots average book-to-market ratios for the Big Value and Big Growth portfolios.

[13] In the Internet Appendix, we report average and median values for fundamental characteristics: size, B/M, investment, profitability, and market beta—across different portfolios. Within the Big Value portfolio, heavy emitters are marginally larger than light emitters in a statistically significant sense, but both groups clearly fall within the 'large-cap' category by conventional asset pricing standards. Their B/M ratios are also economically similar: the median B/M is 0.87 for heavy emitters and 1.00 for light emitters. While this difference is statistically significant, it is economically negligible, especially when contrasted with the much lower average (median) B/M of 0.22 (0.19) for Big Growth stocks. Notably, despite not explicitly matching on these dimensions, in our sample, Big Value heavy and light emitters exhibit statistically indistinguishable investment rates, profitability, and CAPM beta coefficients. It is important to note that our empirical strategy relies on relative changes in returns over time. As long as portfolio characteristics remain relatively stable (which they do) we do not require heavy and light emitters to be identical along every dimension. That said, it is a notable strength of our sample that the two portfolios are closely matched on many key fundamentals.

[14] There is a subtle caveat: heavy emitters in the Value portfolio may be there precisely because they were already discounted (potentially due to their heavy emissions), implying that higher required returns may already be priced in. Our question is narrower. Even if some heavy emitters landed in the Value portfolio because of their pollution-related discounting, we ask whether they earn an *incremental* transition-risk premium beyond the average Value premium. In other words, do they earn a *special* premium due to

about expected returns from realized returns is challenging, as realized returns are noisy and sample-dependent, especially when constrained by a limited time series.[15] Nevertheless, as a first pass, we examine realized returns, beginning with the Pástor et al. (2022) sample period 2012–2020 to align with the existing literature. Examining the returns of Big Value heavy-emitter and light-emitter portfolios, we find that heavy emitters significantly underperformed between 2012 and 2020, losing an average of 7.6% per year. This result is consistent with the results in Pástor et al. (2022) who also find that brown firms underperformed, despite us using a different comparison group for the brown firms and a different way of categorizing brown firms. However, extending the Pástor et al. (2022) sample period by three additional years to the end of 2023 eliminates the average underperformance of Big Value heavy emitters, as these firms had very high returns during the 2021–2022 high-inflation period, particularly following the onset of the war in Ukraine.[16] Similarly, extending their sample backward to July 2006 also eliminates the significant underperformance of Big Value heavy emitters. Examining realized returns over the full sample period (whether raw or risk-adjusted) we find no statistically significant differences in average performance between the two portfolios. Therefore, based on realized returns, we find little evidence during our sample period that heavy emitters earn an incremental premium on average.

Given the difficulty of inferring expected returns from realized returns, we turn instead to expected return proxies: the Implied Cost of Capital (ICC) – computed as the average of four different methods – as well as the option-implied expected return lower bounds from Martin and Wagner (2019). We examine both value-weighted and equal-weighted versions of these proxies to ensure that our results are not unduly driven by a few large firms and draw similar conclusions across weighting schemes. Consistent with the notion that climate concerns were not particularly salient prior to the 2015 Paris Agreement, we find that ICCs and option-implied expected returns were essentially identical for heavy and light emitters within the Big Value portfolio before 2015 (interestingly, average realized returns from 2006 to 2015 were also nearly indistinguishable across the two portfolios). From 2015 to 2020, the expected return proxies for the Big Value heavy-emitter portfolio rose significantly relative to those of the Big Value light-emitter portfolio. In other words, during that period, there

climate-related risks, or do they simply earn (or are expected to earn) the same return as other Value firms?

[15]Our full sample period runs from 2006 to 2023, with the start date dictated by the availability of emissions data from Trucost. While Trucost data coverage improves substantially after 2016, large firms are consistently covered throughout the sample period: coverage for the Big Value and Big Growth portfolios we analyze averages around 90%.

[16]In our sample, there are periods when the heavy-emitter Value strategy sometimes outperforms the light-emitter Value strategy. However, these instances are typically associated with commodity price booms (likely reflecting favorable changes in expected future cash flows) and are not persistent.

was an additional ex ante premium associated with heavy-emitter firms in the Big Value portfolio, a pattern consistent with the empirical findings of Bolton and Kacperczyk (2021, 2023), who document priced transition risk in samples covering this period. Notably, the rise in ICCs for heavy emitters coincides with their significant underperformance, which is consistent with repricing, as required returns increased.[17] However, following the COVID period, we observe a marked convergence in expected return proxies between Big Value heavy and light emitters. Hence, while expected return proxies were temporarily higher for Big Value heavy emitters between 2015 and 2020, they have since aligned. In sum, we find little evidence of a persistent "brownium" (i.e., a consistent expected return premium for heavy emitters within the Big Value portfolio), but we do see a temporary one. This pattern is most consistent with models that predict a time-varying transition risk premium (e.g., Bansal, Wu, and Yaron, 2022).

Our ability to observe the fading of the brownium post-COVID stems from our empirical strategy of comparing heavy emitters to light emitters within the same Value portfolio. By holding constant key firm fundamentals this approach isolates the role of emissions while avoiding the confounding effects that arise when comparing Value and Growth stocks. Given that most commonly used 'green' portfolios often correlate highly with Big Growth,[18] had we instead compared heavy-emitting Value firms to light-emitting Growth firms we would have incorrectly concluded that a substantial brown–green spread persists. Additionally, while we observe a statistically and economically significant, but temporary, brownium between 2015 and 2020, our choice of comparison group with similar fundamentals attenuates the magnitude of this effect. In contrast, had we instead compared Big Value heavy emitters to Big Growth light emitters, the estimated change in value-weighted (equal-weighted) ICC spreads between the Paris Agreement and the start of the COVID pandemic, for example, would have been approximately 1.90% (1.60%), rather than 1.39% (0.78%). Our empirical design thus offers a simple, intuitive, and visual framework for gauging whether an incremental transition risk premium exists, while transparently controlling for other key covariates, which is a valuable feature given the active and important debate in the literature.

Lastly, using our approach, we revisit the recent outperformance of Growth over Value stocks and the apparent disappearance of the value premium over the last decade. Pástor

[17] Using an event study around the Paris Agreement, we find that expected return proxies respond to rising climate concerns, even after controlling for oil price shocks, which supports the narrative that repricing was driven by increased salience of climate-related news.

[18] Many commonly used green classifications, like those based on E scores, tend to align with characteristics of large Growth firms. As a result, portfolios constructed on the basis of such classifications (especially when value-weighted) can be heavily tilted toward Growth stocks.

et al. (2022) argue that, given a large share of Value stocks are brown and Growth stocks are typically green, the outperformance of Growth may be attributed to the poor performance of brown firms. However, while we find that the underperformance of Value stocks, particularly from 2012 to 2020, can indeed be partially attributed to the poor performance of heavy emitters within the Value portfolio, this is not the whole story. To investigate further, we examine the difference in realized returns and expected return proxies between the Big Value and Big Growth light-emitter portfolios. As noted earlier, the light-emitter Value portfolio is just as green as the Growth portfolio. This comparison allows us to study firms with similar climate characteristics but differing fundamentals, helping to isolate whether return differences are driven by green preferences or by other economic forces. If the recent return gap between Growth and Value were driven exclusively by investors' preferences for green firms, we should observe little difference in returns between these two light-emitter portfolios. Yet, we still find that Big Growth light emitters earned higher realized returns (particularly risk-adjusted returns) than their Big Value light-emitter counterparts, both over our full sample and even within the 2012–2020 period examined by Pástor et al. (2022). Notably, the Big Growth light-emitter portfolio also exhibits consistently lower ICCs and option-implied expected return lower bounds than its Big Value counterpart. Hence, *ex ante*, the Value premium appears intact. Moreover, we observe that the ICC spread has widened in recent years, as Growth firms' ICCs declined relative to light-emitter Value firms, which is a pattern that may help explain their temporary outperformance in realized returns. Our findings thus call into question the hypothesis that the recent outperformance of Growth over Value stocks (coinciding with a decline in required returns for Growth stocks) can be explained by Growth stocks being predominantly green and investors' rising preference for greenness. Another possible explanation is that creative destruction, fueled by technological innovation, has simply benefited newer, growing firms (many of which happen to be labeled green by conventional metrics) at the expense of older incumbents.

Related literature Krueger, Sautner, and Starks (2020), surveying large institutional investors, find that climate risk is viewed as material both for their portfolios and their reputations (see, Matos, 2020, for a literature survey on responsible institutional investing).[19]

[19]Starks (2023) emphasizes the importance of understanding why investors care about the Environmental, Social, and Governance (ESG) characteristics of their portfolio holdings. While some investors prioritize financial returns, others are motivated by the desire to align their investments with personal or ethical values. Our findings contribute to this discourse by offering insights that are relevant to both types of investors: those driven by pecuniary objectives and those who also consider nonpecuniary aspects when investing in portfolios exposed to climate risk.

Atta-Darkua, Glossner, Krueger, and Matos (2024) find that climate-conscious investors reweigh their portfolios away from carbon emitting firms.[20] Beyond the finance literature, there is concern that heavy emitters pose unique and significant risks, particularly due to their potential for substantial losses during carbon transitions (see, e.g., Griffin, Jaffe, Lont, and Dominguez-Faus, 2015; Trinks, Scholtens, Mulder, and Dam, 2018; Semieniuk et al., 2022; Callahan and Mankin, 2025). Our paper focuses on these heavy carbon emitters, examining the portfolios in which they appear and whether there is a consistent incremental risk premium associated with holding these stocks.

Our research contributes primarily to the empirical work on the pricing of climate change risk. While there is theory predicting that brown firms should command a premium due to their exposure to transition risks (Heinkel et al., 2001; Pástor et al., 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Zerbib, 2022), the empirical evidence on the performance of green versus brown stocks is mixed. While there is convincing evidence that climate news impact stock prices (e.g., Engle, Giglio, Kelly, Lee, and Stroebel, 2020; Pástor et al., 2022; Ardia, Bluteau, Boudt, and Inghelbrecht, 2023), there is little consensus of whether there is additional persistent premium associated with transition risk. Notably, Bolton and Kacperczyk (2021, 2023), studying realized stock returns in a panel regression framework, conclude that there is a significant carbon premium both in the U.S. and internationally. In contrast, Aswani et al. (2024) and Zhang (2025) raise concerns about the empirical specification in Bolton and Kacperczyk (2021), and after making adjustments, Aswani et al. (2024) find no evidence of a premium, while Zhang (2025) finds that greener stocks actually outperformed during her sample period.[21] Similarly, Pástor et al. (2022) document a seemingly counterintuitive, significant outperformance of green stocks relative to brown stocks during the period from 2012 to 2020, but caution that this outperformance is driven by unexpectedly strong increases in environmental concerns, rather than high expected returns.[22] Sautner et al.

[20] Hartzmark and Shue (2024), however, highlight that such 'sustainable' investing strategies may be counterproductive, in particular when focusing on percentage changes in emissions. Firms classified as green based on their carbon intensities offer limited scope for further improvement in their environmental impact, whereas brown firms have greater potential for meaningful change.

[21] Bolton and Kacperczyk (2024) subsequently respond to these critiques.

[22] Relatedly, Ardia et al. (2023) find that between 2010 and 2018, green firms outperformed brown firms during times of unexpected increases in climate change concerns. Moreover, Bauer, Huber, Rudebusch, and Wilms (2022) document that, across G7 countries, green stocks have generally outperformed brown stocks during this period. In turn, Van der Beck (2021) uses fund-flow data to show that, during the period from 2015 to 2021, the outperformance of 'green' portfolios was strongly driven by the price impact from flows towards ESG funds. Hartzmark and Sussman (2019) also find that investors value sustainability, as demand for mutual funds varies with their sustainability ratings. An alternative perspective is provided by Atilgan, Demirtas, Edmans, and Gunaydin (2024), who argue that the observed carbon premium in

(2023b), studying S&P 500 stocks, find no carbon premium when examining realized returns. Eskildsen et al. (2026) provide an exhaustive and recent overview of studies reporting positive, negative, or no differences in the past performance of green versus brown assets.[23] Additionally, those authors find that replicating previous studies using an extended sample period reverses some of the original results.

Given the short sample period for pollution and E-scores data, along with the potential for a regime shift following the Paris Agreement, ex post realized returns may be unreliable estimates of expected returns. Therefore, we primarily rely on alternative expected return proxies, using ICC (Gebhardt, Lee, and Swaminathan, 2001; Claus and Thomas, 2001; Easton, 2004; Ohlson and Juettner-Nauroth, 2005; Mohanram and Gode, 2013) and option-implied measures (Martin and Wagner, 2019). This approach aligns with studies analyzing the performance of polluting firms using similar methods, including Pástor et al. (2022) and Eskildsen et al. (2026) for ICC, as well as Sautner et al. (2023b) for both ICC and option-implied measures. Pástor et al. (2022) estimate substantially lower expected returns for green stocks than for brown stocks using ICC.[24] Eskildsen et al. (2026) propose a different green score specification and conclude that green stocks have lower ICCs than brown stocks, although the difference is much smaller than in Pástor et al. (2022).[25] Sautner et al. (2023b), using Fama-McBeth regressions at the stock-month level within the S&P 500 universe, document a small and variable premium for brown stocks in expected return proxies, with elevated premiums observed prior to 2014. We find that heavy emitters (brown) firms are predominant in Value portfolios, but are essentially absent from Growth portfolios, making comparisons between brown and green stocks difficult without appropriately accounting for the differences in their fundamental characteristics. As previously noted, accounting for these fundamental differences may be non-trivial, as Value and Growth stocks differ non-linearly (e.g., average B/M ratios are five times higher). In contrast to the existing literature, we focus primarily on the heaviest emitters brown firms and look within the Value portfolio (comparing heavy and light emitters) to isolate the effect of emissions on expected returns,

realized returns may be partly attributed to unexpected positive earnings surprises and higher earnings announcement returns, rather than differences in expected returns.

[23]Giglio et al. (2021a) review earlier empirical literature on the pricing of climate risks.

[24]Pástor et al. (2022) also argue that the recent outperformance of Growth stocks over Value stocks is driven by green vs. brown dynamics. However, our results suggest otherwise. We find that the outperformance of Big Growth light emitters relative to Big Value light emitters is unlikely to be driven by differences in greenness, as both portfolios have similar carbon emissions and E scores.

[25]Relatedly, Gormsen, Huber, and Oh (2024) estimate firms' perceived cost of capital from corporate conference calls and show that, post-Paris Agreement in 2015, green firms' perceived cost of capital is lower than that of brown firms.

while keeping fundamentals relatively constant.[26] This setup can be interpreted narrowly as testing for a carbon transition premium within the Value portfolio, still an important question given the prominence of value investing in practice. More broadly, by controlling for key fundamentals in a transparent and intuitive way, our approach also contributes to the wider debate on whether carbon risk is priced. We find no persistent carbon premium among Value stocks, but we do observe a significant, temporary premium around the time of the Paris Agreement, coinciding with rising climate awareness and the surge in ESG investing.

We also relate to the literature that uses portfolio returns to estimate factor exposure and portfolio decarbonization (e.g., Madhavan, Sobczyk, and Ang, 2021; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2021; Bolton, Kacperczyk, and Samama, 2022; Jondeau, Mojon, and Pereira da Silva, 2025), or addresses the carbon footprint of specific investment strategies (e.g., Blitz and Hoogteijling, 2022). More generally, we contribute to the extensive literature on stock market factors (e.g., Fama and French, 1993, 2015; Asness, Frazzini, Israel, and Moskowitz, 2015), particularly studies considering multiple factors (e.g., Hou, Xue, and Zhang, 2020; Chen and Zimmermann, 2021; Jensen, Kelly, and Pedersen, 2022). Our research differs from most existing work in that we examine the precise composition of characteristic-sorted portfolios rather than relying on indirect measures like correlations.

2 Data and variable descriptions

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. We add individual stock ICCs and option-implied expected return lower bounds as proxies for expected returns. 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.[27] For the construction of anomaly portfolios, we use the signals (that utilize CRSP or Compustat data) for 209 anomalies from Chen and Zimmermann (2021).[28]

[26] Our list of brown firms, defined by carbon intensity, is similar to the list of firms using absolute pollution and MSCI E scores used in other studies.

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

[28] www.openassetpricing.com

2.1 Sample construction

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. For the construction of Fama-French portfolios, we follow Fama and French (1993), Fama and French (2015), and the methodology provided on Ken French's website (the Internet Appendix provides details).

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.[29] Finally, implied cost of capital and option-implied expected return lower bound data is merged by PERMNO. 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 literature.

2.2 Emissions data

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 responsibility, sustainability, or environmental reports, the CDP, EPA filings), and company websites (S&P Global, 2020b). 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.[30]

The Internet Appendix shows Trucost data coverage. Starting in fiscal year 2005, Trucost covered 843 CRSP firms. Coverage expanded in 2016 to include mid- and small-cap companies.[31] We observe an increase in the number of firms covered, from an average of

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

[30]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).

[31]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

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 coverage differs across these periods, we typically report separately results for the period 2016 onward and the full sample period. Notably, as shown in Section 3.2, persistence in firm carbon-intensity rankings is high, hence, in order to increase the available sample among smaller firms, we use backfilled pollution data during the period 2005–2016 for the firms with missing pollution data.[32]

When analyzing in Section 4 the distribution of heavy emitters across characteristics-sorted portfolios, such as value and growth strategies, we rely on concurrent emissions data. Specifically, for each year we identify heavy emitters at the end of June using the Trucost emissions data for the reporting period that includes that month.[33] In our return analysis in Section 5, we construct tradable portfolios at the end of June based solely on emissions data from the previous year. This assumes that emissions data become available to investors only with a delay of six months following the end of the reporting period.

2.3 Expected return proxies

2.3.1 Implied cost of capital (ICC)

We follow Mohanram and Gode (2013), Lee, So, and Wang (2021), and Eskildsen et al. (2026) and use for each firm the equal-weighted average of the four ICC measures: Gebhardt et al. (2001), Claus and Thomas (2001), Easton (2004), and Ohlson and Juettner-Nauroth (2005). The ICC estimates for the four measures are from Eskildsen et al. (2026).[34]

The Internet Appendix illustrates the coverage with ICC data for the Fama-French Value and Growth portfolios. For our main analysis, which focuses on the Big Value and Big Growth portfolios, coverage averages around 98% in terms of market capitalization and 95%

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. Zhang (2025) further notes that Trucost conducted a review and update of the pre-2008 data in May 2009.

[32] The Internet Appendix shows Trucost data coverage for this backfilled sample.

[33] We consider concurrent emissions data to be the most representative for illustrating the presence of heavily polluting firms in different portfolio strategies. Although such data may not yet have been formally published, substantial changes in firms' emissions rarely come as a surprise to investors. For example, when Eversource Energy, a publicly traded New England utility, sold five fossil fuel power plants in 2018, the associated decline in emissions was known well in advance of the end of the reporting period in December (see the Internet Appendix for details of this case study). Importantly, our results are not sensitive to this choice. We reproduce the tables in Section 4 using lagged emissions data, and the findings remain unchanged.

[34] We provide a brief description of the key details underpinning ICC construction; for more extensive coverage, readers can refer to Eskildsen et al. (2026) and the original papers.

in terms of the number of firms during our sample period.[35]

2.3.2 Option-implied lower bounds

As one of the proxies for expected returns, we use the option-implied expected return lower bounds from Martin and Wagner (2019). Martin and Wagner (2019) develop a non-parametric measure of a stock's expected return, based on the risk-neutral variance of the market and the stock's excess risk-neutral variance relative to the average stock. Their measure can be easily computed from observed index and stock option prices and has been shown to perform well empirically.[36]

We source the data, computed using options with 30-day maturities from OptionMetrics, for S&P 500 constituent stocks from Chabi-Yo, Dim, and Vilkov (2020). The data are daily, and we use the monthly averages of the daily observations as our monthly measure. The coverage for the Big Value and Big Growth portfolios, reported in the Internet Appendix, is adequate (though lower than the ICC coverage), averaging around 90% in terms of market capitalization and 60% in terms of the number of firms over our sample period.

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 often rely on industry-based classification guided by the IPCC's categorization of heavily polluting industries (see, e.g., Choi, Gao, and Jiang, 2020). Although 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).[37] Therefore, we

[35] The average coverage for the Fama-French Small Value and Growth portfolios, which we only use in unreported results, is expectedly lower at 82% and 58% in terms of market capitalization and number of firms, respectively.

[36] There are other option-implied expected return lower bound measures in the literature (e.g., Kadan and Tang, 2020; Chabi-Yo, Dim, and Vilkov, 2023), which are derived under slightly different assumptions. However, empirically, these measures are typically highly correlated, especially at lower frequencies and the portfolio level, which is our primary focus.

[37] The Internet Appendix presents a case study of Eversource Energy, a firm that has significantly reduced its carbon footprint (moving from one of the heavier emitters to a light emitter) but would not be classified as lowering emissions based on industry codes.

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. To classify each firm, we utilize a commonly used measure in practice: carbon intensity, defined as the firm's GHG emissions (measured in metric tons of carbon dioxide equivalent) per \$1 million in revenue ($mtCO_2e/\$M$). Aswani et al. (2024) and Zhang (2025) persuasively argue that carbon intensity is the most appropriate measure to assess carbon performance.[38] 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 argue that the most carbon-intensive 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. Importantly, our approach of sorting based on carbon intensity also captures the largest absolute emitters.

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.[39] 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 to calculate carbon intensities, 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

[38] In the industry, emission intensity has been the standard measure used to assess the carbon exposure of stock indices (see, e.g., S&P Global, 2020a).

[39] 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 are hardest to monitor and its reporting is not standardized and is often incomplete, leading to measurement errors.

and 2, or the sum of Scope 1, 2, and 3 emissions is, on average, 93% and 80%, respectively. Moreover, the overlap with the set of firms ranked by absolute Scope 1 emissions is 70%, and their total emissions represent 96% of the emissions from the top 10% of absolute emitters. Thus, any differences in classification do not significantly impact the tails of the distribution, which is the primary focus of our analysis.

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.[40] We, however, make four adjustments to the industry classification. We use this custom industry scheme solely for the visual summary of carbon intensity across industries, and not in our formal analysis later in the paper. First, we separate Agriculture from Non-Durables because it is one of the most carbon-intensive sectors (Crosignani, Osambela, and Pritsker, 2024).[41] 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.[42] Third, we report Berkshire Hathaway (BRK) separately due to its large emissions, which would otherwise

[40]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.

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

[42]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'.

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.[43] 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 Mining 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 Mining 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.[44]

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 3,810, 487, and 179 mtCO_2e/\$M, respectively, whereas the marginal carbon intensity of the top 20%, top 50%, and bottom 20% drops to 32, 13, and 1 mtCO_2e/\$M, respectively. Given that a typical passenger vehicle emits about 4.6 mtCO_2e per year[45], the carbon intensities of firms below the top decile or quintile of the most carbon-intensive firms are, in economic terms, arguably small.[46] 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 the key factor, as regulations limiting emissions typically target activities with the highest emission levels (see, e.g., detailed discussion in Bolton and Kacperczyk, 2021). 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.

Panel (a) of Figure 3 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

[43]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.

[44]Chittaro, Piazzesi, Sena, and Schneider (2025), also observe substantial within-sector heterogeneity in emission intensities.

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

[46]Hartzmark and Shue (2024) 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.

before flattening out significantly after about the top 10% of the most carbon-intensive firms. Panel (b) provides the exact numbers for a few key cutoffs (the top 5%, 10%, 15%, and 20%). We 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 publicly listed U.S. firms, while the top 10% and 15% account for approximately 92.1% and 94.8% of total GHG emissions, respectively.

Perhaps 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. 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.[47] 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.[48] Notably, while these firms represent a disproportionate share of total GHG emissions, their share of total market capitalization is 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.

Panel (a) of Figure 4 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, Panel (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, within Manufacturing, firms in the top decile of heavy emitters across all industries generate 85% of GHG emissions but represent only about 15% of the sector's market capitalization.

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

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

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.[49] 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 in the top decile, with five manufacturers of internal combustion engines (Ford, GM, Caterpillar, Paccar, and Cummins).[50]

Largest absolute emitters The 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, Transportation, 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 metric tons of CO_2e) of the industry's aggregate Scope 1 GHG emissions.

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.

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

[49] 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.

[50] 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. Interestingly, Sautner, Van Lent, Vilkov, and Zhang (2023a) report that Caterpillar is actually a top producer of green patents, suggesting the company is actively diversifying away from heavy-emitting activities. Nonetheless, the inclusion of a single firm has no bearing on our results.

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. We find that the probability of the 10% of the firms with the highest carbon intensities in a given year to remain in the top decile is 96.5%.[51] Figure A.7 in the Internet Appendix illustrates this persistence in carbon-intensity rankings.

E scores We also 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).[52] 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.[53] Hence, heavy emitters are consistently associated with low E scores, and 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.

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.[54] Climate Action 100+ focuses worldwide on 170 companies critical to the net-zero emissions transition; of these, 38 firms are part of the CRSP sample.[55]

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

[51] Bolton and Kacperczyk (2021) report an autocorrelation for Scope 1 carbon intensity of 0.945.

[52] The raw E scores are as defined in Pástor et al. (2022): Raw E score $= -(10 -$ environmental-pillar-score$) \times$ environmental-pillar-weight $/100$. A higher E score indicates a 'greener' firm.

[53] This relationship is illustrated in Internet Appendix Figure A.8.

[54] 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.

[55] 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 U.S.-headquartered firm, Bunge, a global agribusiness and food company incorporated in Switzerland, is removed from our sample due to our filters.

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. In contrast, Climate Action 100+ tracks GM and Ford, but not Tesla. As we explain in the Internet Appendix, when examining aggregate GHG emissions, private vehicles account for the majority of U.S. GHG emissions in the transportation sector. Hence, internal-combustion engine vehicle manufacturers 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.[56] Therefore, in our benchmark specification, we add these firms to the list of heavy emitters by replacing the five lowest-carbon-intensity firms within the top decile with these five additions.

We then have 31 of the 38 Climate Action 100+ firms that 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 the car and truck manufacturers (Ford, General Motors, Caterpillar, and PACCAR) and the heavy equipment and automotive firm (Cummins) that we include in our list of heavy emitters. The seven 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 the primary concern for the two military hardware manufacturers.[57] Also excluded is the multinational conglomerate 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, with Colgate-Palmolive and Walmart receiving favorable evaluations from Climate Action 100+ for their climate practices, indicating that they may not obvious offenders and may be less exposed to transition risks. 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 (reported in the Internet Appendix). This analysis again shows that our method effectively identifies most of the firms vulnerable

[56]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 to bypass or disable emissions controls on 960,000 Dodge and 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).

[57]Boeing is also involved in military and space activities. More importantly, 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.

to carbon transition risks, aligning closely with the coverage provided by the TPI Centre.

3.3 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 heavy emitters and the remaining firms. The average carbon intensity of the top 10% most carbon-intensive firms is 618.0 metric tons (mt) of CO_2e per million dollars in revenue, compared to only 16.4 mtCO_2e/\$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. Moreover, we observe 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, though the data coverage for E scores is about 20-30% lower than for the emissions data used in our analysis.

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 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). Notably, we observe significant differences in B/M ratios, irrespective of whether we compare means or medians, with heavy emitters having a 36% higher mean book-to-market ratio than the remaining firms. These patterns are consistent with the findings of Bolton and Kacperczyk (2023), who, in a global sample of firms, show that higher absolute levels of GHG emissions are associated with higher book-to-market values. Additionally, 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.[58] We

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

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 almost identical. On the other hand, heavy emitters appear, on average, to be more profitable when examining operating profits (scaled by book equity). The volatility and CAPM (market) betas of heavy emitters' stock returns is comparable to that of other firms' stocks.

4 Value and Growth styles/factors

In this section, we first analyze the distribution of heavy emitters in the Fama-French book-to-market-sorted portfolios (Value-Growth) by evaluating the proportion of heavy emitters in each portfolio. We then examine the properties of other value and growth portfolios. The discussion of other factor portfolios such as those based on investment and profitability characteristics of firms is deferred to Section 6.

4.1 Heavy emitters in the Fama-French Value/Growth portfolios

Table 2 presents the market capitalization share of heavy emitters in Fama-French book-to-market-sorted portfolios. Since these portfolios are value-weighted in practice, we focus on the value weights, and present the firm count shares in the Internet Appendix.

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. Book-to-market-sorted portfolios are constructed using 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 (we denote the conditional means as $\bar{w}_v^k$, with $k =$ Small or Big).[59]

Examining the results in Table 2, 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

[59]In Internet Appendix Table A.1, we report that heavy emitters represent, on average, 13% of the Big portfolio (t-stat $= 1.14$ for the test of whether the mean is different from the unconditional mean $\bar{w}_v$), and 8% of the Small portfolio (t-stat $= -8.05$ for the test of whether the mean is different from $\bar{w}_v$).

= −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), with the difference, 10%, being statistically significant (t-stat = 15.62).[60] Looking at the share in terms of the number of firms, we observe similar results (see, the Internet Appendix). To ensure the observed patterns are not driven by the recent sample period, we repeat the analysis using the extended sample (2005–2023), incorporating some backfilled emissions data for firms without timely emissions information as discussed in Section 2. While the exposure of Value portfolios to heavy emitters is slightly reduced in the longer sample (e.g., Big Value portfolio holds 34% in heavy emitters on average), all patterns remain consistent. Lastly, combining these portfolios to form the Fama-French 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), showing that a regression of their green-minus-brown factor on the Fama-French exhibits a significant negative loading on the HML factor.

In summary, our analysis reveals a clear and consistent pattern: heavy emitters are disproportionately represented in Value portfolios and significantly underrepresented in Growth portfolios. Naturally, this aligns with the observed association between emissions and book-to-market ratios, as shown earlier in the descriptive statistics and documented by Bolton and Kacperczyk (2023), alongside the common intuition that Value stocks are often found in older, capital-intensive, and potentially polluting, industries. However, our results highlight several important points. First, while there is a non-linearity in the distribution: where heavy emitters are virtually absent in Growth stocks, they are substantially represented in Value stocks. Second, this pattern holds true for both large and small stocks, but it is the Big Value portfolio that is most exposed to heavy emitters. It is also worth noting that not all Value stocks are heavy emitters. In fact, the majority of Value stocks are not heavy emitters, and as we will show later, their emissions and other green credentials are comparable to those of Growth stocks. We leverage these patterns in our subsequent analysis of returns.

[60] 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 heavy emitters in the Small Value portfolio is a lower bound, as some unclassified firms may actually be heavy emitters.

4.2 Other Value and Growth portfolios

We also analyze 161 anomaly portfolios from Chen and Zimmermann (2021) with adequate coverage in our U.S. sample. Our focus in this sub-section is on anomaly portfolios related to value/growth, with additional discussion of portfolios based on investment, profitability, and others deferred to Section 6 and the Internet Appendix. We group the anomaly strategies into these themes based on prior literature.

Table 3 presents the results for the value-growth-type anomalies. We observe a consistent trend: heavy emitters are more commonly found in the long leg (value) portfolios. Using December market equity to compute book-to-market ratios, as in Fama and French (1992), instead of June market equity, as in Fama and French (1993), illustrates that our findings are robust to minor adjustments in the sorting criteria. The proportion of heavy emitters in the high book-to-market (value) portfolio 5 is 36%, compared to the low book-to-market (growth) portfolio 1, with only 2%, which is essentially the same as in Table 2. Next, we examine portfolios sorted on tangibility. We observe that there are almost no heavy emitters among stocks with a low fraction of tangible assets in portfolio 1 (1%), and the difference in proportion between the high-tangible-asset portfolio 5 and portfolio 1 is positive and highly statistically significant for both the main and extended sample (shown in the last column). This is in line with the fact that a large 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.[61] However, in our sample, we find that 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 classified as heavy emitters, such as Energy firms, dominate portfolio 4 during this period. Thus, the difference between low-tangible-asset portfolio (portfolio 1) and high-tangible-asset counterpart is even starker when we consider portfolio 4, instead of portfolio 5, as the high-tangible-asset portfolio. In the same spirit, 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

[61] In Section 3.2, we discuss the inverse relationship between high carbon intensity and low E scores.

(2016-2023) and the extended sample period (2005-2023). The proportion of heavy emitters in portfolios with high sales-to-price ratios from Barbee, Mukherji, and Raines (1996) and high operating cash flow-to-price ratios from Desai, Rajgopal, and Venkatachalam (2004) is also significantly higher (the t-statistics for the difference test between Long and Short shares are again shown in the last column). The results for cash flow-to-market value from Lakonishok, Shleifer, and Vishny (1994) point in the same direction, though the pattern is weaker than in the other portfolios. 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 1-3 with the highest enterprise multiples. Similarly, the proportions of heavy emitters in portfolios sorted on earnings (earnings-to-price ratio from Basu (1977), earnings forecast-to-price from Elgers, Lo, and Pfeiffer (2001), and long-term EPS forecast from La Porta (1996)) confirm the pattern: heavy emitters tend to be more prevalent in portfolios with higher earnings-to-price and earnings forecast-to-price ratios, and lower EPS forecasts, characteristics typically associated with value firms. Furthermore, value stocks tend to have shorter equity durations 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, 1979) portfolios. Finally, employment growth from Belo, Lin, and Bazdresch (2014), which captures a different dimension unrelated to the balance sheet or income statement, also supports the main finding: heavy emitters are overrepresented in value portfolios, particularly in portfolio 5 with low employment growth.

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.

5 Returns

In this section, we investigate whether investors receive or expect to receive compensation for their exposure to transition risk when holding heavy emitters. We conduct this analysis using firms within the Fama-French Big Value and Big Growth universe. We divide firms into heavy and light emitters (where light emitters are defined as firms not classified as heavy emitters) based on carbon intensities for their most recent reporting period, lagged by six months.[62] We then compare the subsequent realized returns and expected return proxies of portfolios consisting of heavy versus light emitters.

We focus on the Big Value portfolio because (1) heavy emitters represent, on average, around 35% of market capitalization, allowing us to compare two portfolios of similar importance.[63] (2) For reducing total global greenhouse gas emissions, the Big Value portfolio is particularly relevant, as the absolute emissions of its firms are three times those of the Big Growth portfolio, even though its market capitalization is only one fifth as large (the exact numbers are reported in the Internet Appendix). (3) We have almost complete coverage of big firms in ICC and option-implied data that we use to proxy for expected returns, as well as emissions data.[64] Additionally, coverage based on reported emissions data for heavy emitters in the Big Value portfolio is 91%, thereby mitigating concerns raised by Aswani et al. (2024) regarding the use of estimated emissions data. (4) In our sample, our Big Value heavy emitter and low emitter portfolios also align on key fundamental characteristics such as size, B/M ratios, investment, profitability, and market beta.[65] In other words, we compare two portfolios with similar fundamental characteristics, but different carbon emissions.

We then compare the realized and expected returns of light emitters in Big Value with those in Big Growth to establish a benchmark value versus growth spread that should be largely immune to carbon transition risk considerations, and contribute to the ongoing discussion in the literature on whether the outperformance of growth relative to value strategies (i.e., the apparent disappearance of the value premium) in the past decade could be explained by investors' green preferences and carbon transition risk considerations (e.g., Pástor et al., 2022). We focus on light emitters as they represent a significant share of the Value portfolio

[62] More specifically, for firms with fiscal year ending in December, we use the previous year's carbon intensity when sorting firms into Fama-Fench portfolios end of June (for firms reporting in March or June, we assume that information about carbon intensities is not yet available to investors by end of June and also use the previous years' emissions data).

[63] In contrast, heavy emitters represent, on average, only around 12% of the Small Value portfolio.

[64] As shown in the Internet Appendix, the ICC data (and especially the options data) have limited coverage for small firms, making inference for that segment difficult.

[65] For this analysis, we exclude firms from the utility sector due to their distinct return behavior and low market betas, with government oversight often influencing their pricing and investment decisions. Internet Appendix Table A.4 reports average and median values for size, B/M, investment, profitability, and market beta across different portfolios. Within the Big Value portfolio, heavy emitters are statistically larger than light emitters, though both groups fall squarely within the Big stock category by convention standards. The median B/M ratios are also economically similar (0.87 for heavy emitters versus 1.00 for light emitters), despite the difference being statistically significant. By contrast, Big Growth stocks exhibit much lower B/M ratios, with average (median) values five times smaller at around 0.22 (0.19). Big Value heavy and light emitters also have statistically indistinguishable average and median investment rates, profitability, and CAPM betas. Additionally, at the portfolio level, the two subgroups exhibit similar MKT loadings over the full sample period.

and constitute the majority of Growth portfolios, allowing us once again to compare two broad portfolios.[66] Specifically, this analysis controls for firms' carbon emissions, comparing two portfolios with similar emissions, but different fundamental characteristics. We emphasize that emissions data are solely used to classify firms into heavy and light emitters and we do not include them directly in our tests of the existence of a premium for transition risk. This approach mitigates the methodological challenges highlighted by Kacperczyk (2026) in estimating transition risk premia within a standard cross-sectional asset pricing framework, as well as the concerns raised by Aswani et al. (2024) that estimated emissions may be correlated with financial fundamentals.

5.1 Carbon intensity, absolute pollution, and E scores comparison

In this sub-section, we first reiterate that heavy emitters in the Big Value portfolio are much more polluting than the light emitters in the Big Value portfolio, and then we demonstrate that light emitters in the Big Value portfolio are as 'green' as the light emitters in the Big Growth portfolio. Table 4 first compares the value-weighted carbon intensity of heavy and light emitters in Big Value. The carbon intensity of heavy emitters over the main sample period 2016-2023 (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),[67] and E scores are substantially lower (worse) for heavy emitters compared to light emitters.

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 difference in Scope 1 carbon intensities between light emitters in the Big Value portfolio is not statistically significant compared to that in the Big Growth portfolio for the main sample period 2016-2023, and are actually smaller in the sample period 2005-2023 (t-stat = -4.04). This result also holds when Scope 2 emissions during the 2016-2023 period are included to compute carbon intensity. For the extended sample

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

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

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, 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.[68] In conclusion, on all GHG emission metrics and E scores, the light emitters in the Big Value portfolio are as 'green' as the light emitters in Big Growth.

5.2 Realized returns

Figure 5 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). We also include the cumulative returns of the Big Growth portfolio (dashed blue line). Panel (a) begins in January 2012, aligning with the sample period in Pástor et al. (2022), and Panel (b) presents returns over our full sample period 2006–2023.

Comparing heavy and light emitters within the Big Value portfolio during the Pástor et al. (2022) sample period, we observe that heavy emitters have significantly underperformed. Table 5(a), Columns (1)–(4), provides formal evidence: between 2012 and 2020, Big Value heavy emitters underperformed their light-emitting counterparts by an average of 7.57% per year, a difference that is statistically significant at the 10% level. Controlling for MKT in Column (2) renders the average alpha more negative and statistically significant. Adding CMA and RMW does not materially change the results.[69] It is worth highlighting

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

[69]To avoid spurious relationships, we do not include SMB and HML, as the two portfolios are already matched on size and book-to-market. We note that the positive and significant loading on MKT beta is largely an artifact of the COVID-period outlier. Excluding 2020 in Column (4) yields a negative and statistically significant alpha of -9.43% (t-stat = 1.65), while the MKT loading drops to 0.13 and becomes statistically insignificant. Similarly, over the longer sample period reported in Columns (9)–(12), we do not observe any meaningful difference in market betas. The coefficient on CMA is positive and statistically significant across all specifications, indicating that Big Value heavy emitters exhibit greater exposure to the CMA factor than their light-emitting counterparts. However, as shown in the last column of Table 8, the

that this result is consistent with Pástor et al. (2022), who also find that brown firms underperformed, despite employing a different classification for brown firms and, importantly, a very different comparison group.[70] However, extending the Pástor et al. (2022) sample period by three additional years to the end of 2023 (Columns (5)–(8)) eliminates the average underperformance of Big Value heavy emitters (the alpha is no longer significantly different from zero) as the heavy emitters experienced exceptionally high returns during the 2021–2022 high-inflation period, outperforming their light-emitting counterparts by an average of 40.73% annually, particularly following the onset of the war in Ukraine. Similarly, extending their sample backward to July 2006 (Columns (9)–(12)) also eliminates the significant underperformance of Big Value heavy emitters. Examining realized returns over the full sample period (whether raw or risk-adjusted) we find no statistically significant differences in average performance between the two portfolios Although realized returns sometimes show periods where heavy emitters appear to outperform[71], the cumulative returns of the two sub-portfolios are nearly identical from 2006 until the Paris Agreement, and again from that point until the onset of the COVID crisis. Thus, based on realized returns, we find little evidence that heavy emitters earn a premium on average during our sample period.

We also observe the well-documented strong performance of the Big Growth portfolio in recent years (see, e.g., Israel, Laursen, and Richardson, 2020). A key issue in both the academic literature and practice has been the apparent disappearance of the value premium, particularly pronounced during the sample period examined by Pástor et al. (2022). For example, the average annualized return for the Fama-French HML factor was −5.12% between

CMA factor has a positive exposure to heavy emitters, suggesting that this difference in exposure may be at least partly mechanical.

[70] Pástor et al. (2022) compare their set of brown firms to those with the highest MSCI E scores, which are typically dominated by Growth firms, particularly in value-weighted portfolios. To take just one anecdotal example, Meta Platforms received a perfect 10/10 E score from MSCI in 2023.

[71] To explore the potential drivers of the return spread dynamics between heavy and light emitters, we examine commodity prices over time. In the Internet Appendix, 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, while the correlation between the plotted cumulative return indices is 71%, highlighting that fluctuations in commodity prices are a potential driver of the temporary divergence in 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 exacerbated by the onset of the war in Ukraine, is associated with strong outperformance of the heavy emitters. The opposite occurred during the pandemic in early 2020, when the heavy emitters appeared to underperform. This result is in line with Bansal et al. (2022) who show that socially responsible investments outperform in recessions. These patterns also align with the study of Shi and Zhang (2024), who find that oil price changes help explain fluctuations in the 'greenium' (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).

2012 and 2020. Pástor et al. (2022) rightly point out that part of the explanation for the disappearance of the realized value premium lies in the poor performance of brown stocks, which constitute a large share of the Value portfolio during that period. As we show above, this is indeed a significant part of the story. However, it is not the whole explanation. When we compare the average realized returns between Big Value and Big Growth light emitters, which are similarly 'green', we find that Growth stocks still outperformed, albeit by a smaller margin, and primarily on a risk-adjusted basis. Table 5(b) reports the regression results. Focusing on the 2012–2020 period in Columns (1)–(4), we find that the Big Growth light emitter portfolio outperformed the Big Value light emitter portfolio by 3.92%, although this difference is not statistically significant. However, once we control for MKT (an important adjustment given that Growth stocks tend to have lower market betas than Value stocks) we observe a statistically significant alpha of 8.75% (significant at the 10% level). Considering different sample periods preserves the general pattern: Big Growth light emitters had statistically significantly higher risk-adjusted realized returns than Big Value light emitters, particularly when the COVID period is included. This suggests that even after abstracting from brown firms, the value premium does not reemerge in realized returns. Importantly, both portfolios consist exclusively of low-emission firms that, as shown earlier, are equally 'green' on average. Thus, the return differential cannot plausibly be explained by emissions exposure, shifts in investor preferences, or green-versus-brown dynamics.

5.3 Expected returns

Given the relatively short history of pollution data, E scores, and other transition risk indicators, it is difficult to draw inferences about expected returns based solely on realized returns. We therefore turn to forward-looking proxies to analyze investors' return expectations, focusing on the ICC and option-implied expected return lower bounds.[72] Although conceptually distinct and based on different information sets (analyst forecasts vs. option prices), both measures provide complementary perspectives on investors' required returns.

5.3.1 Big Value heavy vs. Big Value light emitters

Figures 6 and 8 display the ICC and option-implied expected return lower bounds from Martin and Wagner (2019) over time for the Big Value and Big Growth portfolios. Panel (a) of each figure uses equal-weighted portfolios and Panel (b) uses value-weighted portfolios.

[72]Hereafter, "expected returns" refers to either the ICC, the option-implied expected return lower bounds, or both. For convenience, we often omit the word "proxies."

The equal-weighted portfolio is likely the more relevant benchmark as our objective in this sub-section is to examine the relationship between returns and firms' carbon intensities rather than to evaluate specific trading strategies. Moreover, the value-weighted portfolio can be unduly influenced by few large firms. Within the Big Value portfolio, we compare heavy emitters (solid brown line) and light emitters (solid green line); the dashed blue line corresponds to the expected return proxy for the Big Growth portfolio.

We begin by examining the average difference in ICCs between heavy and light emitters within the Big Value portfolio. Panels A and B of Table 6 present the regression results for the equal-weighted and value-weighted portfolios, respectively.[73] As we observe in Column (1), regressing the ICC difference on a constant over the full sample reveals no meaningful spread: the average difference is 0.27 for the equal-weighted portfolios and −0.11 for the value-weighted portfolios, with neither estimate statistically significant. Indeed, the visual analysis in Figure 6 confirms that the two series track each other closely over most of the sample, particularly before 2015. Similar to the ICC results, Column (1) of Table 7 shows that regressing the option-implied expected return difference on a constant over the full sample yields no meaningful spread: the average difference is 0.63 for the equal-weighted portfolios and 0.08 for the value-weighted portfolios, with neither estimate statistically significant.

However, a noticeable divergence emerges following the Paris Agreement in December 2015, with the ICCs of heavy emitters rising relative to those of light emitters. It is established in the literature (e.g., Bolton and Kacperczyk, 2021) that the Paris Agreement may have marked a turning point in market perceptions regarding carbon transition risk. We therefore test whether a similar shift is reflected in our setting and introduce a dummy variable, Post Paris, which equals one for all months after July 2015.[74] As shown in Column (2) of Table 6, the Post Paris dummy is positive, but not statistically significant, for the equal-weighted portfolio (0.54%, t-stat = 1.26), and, in the case of the value-weighted portfolio. the estimated coefficient is both positive and statistically significant (1.21%, t-stat = 2.38). In Panel B, the constant for the value-weighted regression turns negative (−0.67%) and is statistically significant, while in Panel A the constant in the equal-weighted regression remains near zero (0.03%). This suggests that the negative difference in the pre-Paris period is likely just an artifact of noisy ICC estimates earlier in the sample, which have less influence

[73] The coverage for these ICC measures based on analyst forecasts over the extended sample period 2006-2023 exceeds 95% of market capitalization and number of firms for all four portfolios Big Value heavy emitters, Big Value light emitters, Big Growth heavy emitters, and Big Growth light emitters. The average coverage across the four portfolios is 97.8% (the Internet Appendix shows the coverage).

[74] We lag the start by six months to account for potential forward-looking market reactions as the scheduled Paris meeting and its agenda were known well in advance, even though its conclusions were not certain.

in the equal-weighted portfolio. Similarly, including the Post Paris dummy in Column (2) of Table 7 reveals a large and statistically significant increase in the difference in option-implied expected returns during the Post Paris period: the coefficient on the dummy is 4.77 (t-stat = 2.15) for the equal-weighted portfolio and 4.89 (t-stat = 2.15) for the value-weighted one. The constant in the specification in Column (2), in both panels, turns negative (but statistically insignificant), implying a fairly large increase in expected return during the post Paris period. However, as evident in Figure 8, severe noise around the 2008 financial crisis may be influencing the results. To control for this unrelated volatility, we include a 2008 crisis dummy equal to one during the 2008–2009 NBER recession period. Including the 2008 dummy in Column (3) of Table 7 results in a small positive, statistically insignificant, constant, while leaving the Post-Paris dummy positive and statistically significant in both the equal-weighted and value-weighted portfolios. The magnitude of the coefficients declines to 2.74 and 2.66, respectively, economically more in line with the ICC results.

The Post Paris dummy may be too coarse, as visual inspection suggests several distinct sub-periods following the Paris Agreement. We therefore subdivide it into three mutually exclusive dummies: Paris–COVID, which equals one from July 2015 to December 2019; COVID, which equals one from January 2020 to June 2020 and captures the most intense phase of the pandemic (see, e.g., Augustin, Sokolovski, Subrahmanyam, and Tomio, 2022); and Post COVID, which includes all subsequent observations. As we observe in Column (3) of Table 6, the coefficient on the Paris–COVID dummy is positive and statistically significant, indicating that following the Paris Agreement, the average annual ICC difference rose by 0.78% for the equal-weighted portfolio, significant at the 10% level (t-stat = 1.74). For the value-weighted portfolio, the estimated coefficient is larger: 1.39% (t-stat = 2.48). This increase in the ICC of heavy emitters within the Big Value portfolio coincides with the sharp rise in flows toward sustainable investments during this period (e.g., Van der Beck, 2021; Hartzmark and Sussman, 2019). It also aligns with heightened climate risk concerns among investors, as documented in earnings call transcripts (Sautner et al., 2023a; Gormsen et al., 2024). Moreover, the increase in ICCs for Big Value heavy emitters coincides with their significant underperformance as reported in the previous sub-section, a pattern consistent with repricing as required returns rose. Despite using a very different empirical approach, our findings are consistent with Table 15 of Bolton and Kacperczyk (2021), which documents an increase in the carbon risk premium after 2015, following the Paris Agreement. However, as both the visual inspection of Figure 6 and the regression results suggest, the ICC difference between heavy and light emitters in the Big Value portfolio becomes statistically insignificant in the Post COVID period. While the spread remains slightly positive, it is far less pronounced than the divergence observed around 2017–2018, and much smaller than the growing gap in ICCs we document below between Big Value and Big Growth light emitters.

Turning to the option-implied expected returns and following the same logic as before, we subdivide the Post-Paris dummy into three periods, revealing a similar pattern to the ICC results. We find a positive spread during the Paris-to-COVID period, statistically significant only for the equal-weighted portfolio (2.76, t-stat = 2.01). In fact, the most noticeable difference in Figure 8, compared to the ICC results in Figure 6, is the more pronounced reaction of option-implied expected returns around the time of the Paris Agreement. Similar to the ICC results, the reaction becomes more pronounced when comparing the equal-weighted portfolios in Panel (a), showing that, leading up to the summit in Paris and in its aftermath, the lower bound for the expected returns of heavy emitters exceeds that of light emitters within Big Value.[75] In both panels of Figure 8, the differences between Big Value heavy and light emitters fade shortly thereafter.

For option-implied expected returns, the COVID period stands out for unusually high expected returns, as volatilities reached record highs during that time. Hence, the effect of the COVID period is expected, as the option-implied measure is sensitive to volatility. Moreover, most of the spike in option-implied expected returns for the heavy-emitter portfolio at the onset of the pandemic is likely driven by the dramatic decline in global commerce and trade due to pandemic-related shutdowns, as well as a drop in commodity prices, rather than elevated climate concerns. In the same spirit, while we observe positive but statistically insignificant coefficients on the Post-COVID dummy, visual inspection suggests this is likely driven by residual volatility in the immediate aftermath of COVID, particularly in 2020 and early 2021. From 2022 onward, however, the two series appear nearly identical: between January 2022 and February 2023, the average annualized spread in option-implied expected returns between Big Value heavy and light emitters is just 0.41% for equal-weighted portfolios and 0.13% for value-weighted portfolios, both comparable to the pre-Paris benchmark. Additionally, in several months, the option-implied expected returns of the low-emitting portfolio even slightly exceed those of the high emitters.

[75] The Paris Agreement entered into force on November 4, 2016, after 55 countries, representing at least 55% of global emissions, had ratified it. Before the summit, countries announced their climate action pledges, known as Intended Nationally Determined Contributions (INDCs).

5.3.2 Big Value light vs. Big Growth light emitters

In stark contrast, there is a highly persistent and significant difference between Big Value light emitters and Big Growth light emitters. As shown in Columns (4) of Panel A in Table 6 for the equal-weighted portfolios and in Panel B for the value-weighted portfolios, the average ICC of Big Value light emitters was 2.65% and 2.97% higher, respectively, over the full sample period. Both coefficients are highly statistically significant, with *t*-stats of 7.38 and 10.93. Notably, the difference increased significantly in the post-Paris period, driven by a decline in the ICCs of Big Growth light emitters, as seen in Figure 6, with a particularly sharp drop during the COVID and post-COVID periods.[76] For instance, for the equal-weighted portfolio in Panel A, the estimated coefficients on Paris-COVID, COVID, and Post COVID dummies are 0.81%, 3.95%, and 2.50%, respectively (all significant at the 1% level). We emphasize that both portfolios consist of light emitters, and the results are remarkably similar across equal-weighted and value-weighted specifications. Although the Growth portfolio may include a few distinctive 'green champions' such as Tesla, it is unlikely that the large and persistent difference in average ICCs, or the recent significant widening of this gap between light-emitter Value and light-emitter Growth portfolios, is meaningfully driven by shifts in green investor preferences. The timing of the divergence, beginning shortly after the Paris Agreement, is likely coincidental.

The option-implied expected return lower bounds confirm the result that light emitters in the Big Growth portfolio exhibit persistently lower expected returns than the light emitters in the Big Value portfolio. The differences between the two portfolios in Columns (5)-(8) of Table 7 remain positive (1.49% and 1.77% per annum for the equal-weighted and value-weighted portfolios, respectively) and statistically significant at the 10% level. Moreover, consistent with the ICC patterns, the positive spread between the low-emitter Value and Growth portfolios widens for the equal-weighted portfolio during the post Paris period: driven primarily by the COVID period, and the Post-COVID period.

5.3.3 Robustness: potential effects of backfilling pollution data

Section 2 reports that emissions data coverage is lower prior to 2016. As noted earlier, we backfill missing emissions data for some of the firms in the years prior to 2016 to increase the coverage of smaller firms in our sample. However, this issue does not materially affect

[76] Pástor et al. (2022) document a recent decline in the ICCs of conventionally defined 'green' stocks, but as noted earlier, such classifications frequently overlap with Growth stocks; thus, the patterns we observe are consistent with theirs.

firms in the Big Value or Big Growth portfolios, which are consistently covered throughout the full 2006–2023 sample period. On average, only about one to two percent of Big firms require backfilling. Thus, for the vast majority of relevant firms in our return analysis, we rely on timely reported emissions data. Nevertheless, to guard against potential biases introduced by the backfilling, we replicate our return analysis of this section using only firms with non-imputed emissions data and find quantitatively similar results.

5.3.4 Summary

Taken together, the results suggest that there is no persistent, significant difference in the ICCs or option-implied expected return lower bounds between heavy and light emitters in the Big Value portfolio. Specifically, apart from the temporary divergence between 2015 and 2020 following the Paris Agreement, when heavy emitters commanded a higher premium (consistent with the mixed findings in prior literature), investors typically do not demand a higher expected return from heavy emitters in the Big Value portfolio compared to light emitters in the same portfolio.[77] In other words, there is no additional 'brownium' for the heavy emitters in the Value portfolio and investors can expect to receive similar returns for their heavy and light emitter value stocks.[78] We do, however, find a highly significant, persistent, and growing positive difference in expected return proxies for the Big Value light emitter portfolio compared to light emitter Growth firms. Moreover, we show that these portfolios do not, on average, meaningfully differ in their level of 'greenness', suggesting that this difference may be interpreted as the expected Value premium.

Our findings stand in contrast to Figure 4 in Pástor et al. (2022), which shows a persistent negative equity 'greenium' averaging -1.4% over their sample period November 2012 - December 2020, with the two ICC series never crossing. In our analysis, we do not observe such persistent differences between heavy and light emitters within the Big Value portfolio, the systematic divergence in expected return proxies in our context arises only when comparing light emitters in Big Value to those in Big Growth, a gap likely driven by differences in economic fundamentals (i.e., ex ante value premium) rather than green credentials.

[77] Our results are consistent with Sautner et al. (2023b), studying option-implied expected return proxies and finding a small and fluctuating premium associated with their measure of climate change exposure.

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

6 Other style/factor portfolios

In this section, we assess the prevalence of heavy emitters in the remaining Fama-French factor portfolios, namely investment, profitability, and momentum, as well as other characteristic-sorted anomaly portfolios that do not necessarily fall into the Fama-French themes.

6.1 Investment, profitability, and momentum portfolios

The structure of Table 8 is similar to Table 2, reporting the market capitalization share of heavy emitters in the Fama-French investment and operating profitability factor portfolios.

Investment Examining investment-sorted portfolios (Panel A), 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 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 9, 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.[79] 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 B of Table 8, we examine the operating-profitability-sorted portfolios. We observe that heavy emitters are significantly underrepresented in the Big Robust profitability portfolio, with a market-cap share of 7% (t-stat $= -12.12$ for the test of whether the mean differs from $\bar{w}_v^{\text{Big}}$). However, this pattern is less pronounced when looking at the share by firm count (reported in the Internet Appendix), with heavy emitters comprising 12% of the Big Robust portfolio. This suggests that a small number of large, profitable firms (likely tech firms in recent periods) dilute the market-cap share of heavy emitters in this portfolio. Additionally, heavy emitters appear 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 of the number of firms (reported in the Internet Appendix), with the difference in shares of heavy emitters between Robust and Weak portfolios being in the same direction but not statistically different from zero in our main sample.

In contrast, among Small stocks, heavy emitters are overrepresented 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 underrepresented 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 differenc decreases to 3% in the extended sample period, but remains statistically significant).

Momentum As a type of placebo test, we examine momentum-sorted portfolios. Given the high turnover in momentum strategies, heavy emitters should be equally likely to appear in any momentum decile ex ante, with shares roughly reflecting their underlying size buckets. Consistent with this expectation, we find no meaningful difference in the concentration of heavy emitters between momentum winner and loser portfolios.

[79] 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).

6.2 Style/factor portfolios beyond the Fama-French themes

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. We include only those anomalies for which we have adequate emissions data coverage. Additionally, we report only the findings for anomalies where distinct patterns in the proportions of heavy emitters are evident across portfolios during our main and extended sample periods. Summarizing the findings, heavy emitters are concentrated in portfolios with undesirable traits such as low cash-to-assets ratios, high net debt, 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.

7 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 carbon-intensive firms (heavy emitters) account for over 90% of all Scope 1 emissions from publicly listed U.S. companies. Our analysis shows that heavy emitters are disproportionately concentrated in value-oriented strategies; making up roughly 35% of value of the Fama-French Big Value portfolio, while being largely absent from Growth portfolios.

Given the high concentration of heavy emitters in the Big Value portfolio, it is critical for investors to understand whether they are compensated for holding such firms. Focusing on the Big Value portfolio allows us to isolate the role of emissions while holding key firm characteristics constant. Rather than comparing fundamentally different firms across the Value–Growth spectrum, our approach compares heavy and light emitters within the Fama-French Big Value portfolio, two groups that closely match on fundamentals. This empirical strategy enables a clean and intuitive test of whether brown firms earn an incremental transition-risk premium beyond the average Value premium, or whether their returns simply reflect standard value-related exposures.

Examining realized and expected returns of heavy versus light emitters within the Big

Value portfolio, we find that from 2006 until the 2015 Paris Agreement, both groups earned similar average returns and exhibited comparable expected return proxies, consistent with the view that climate transition risk was not yet salient. Between 2015 and 2020, heavy emitters underperformed, accompanied by a notable rise in their expected return proxies, consistent with a repricing of transition risk and the growing prominence of climate concerns documented in the literature. After the COVID period, however, expected return proxies for heavy and light emitters have converged, suggesting that any transition-risk premium is not persistent. At least within the Value portfolio, there is no clear evidence of sustained incremental compensation for holding high-emitting firms beyond the value premium.

We also compare Big Value and Big Growth light emitter portfolios (stocks of similar 'greenness' but different fundamentals), finding that Big Growth light emitters consistently exhibit lower implied costs of capital and option-implied expected returns than their Value counterparts. This suggests that the ex ante value premium remains embedded in expected return proxies. However, over the past decade, Big Growth light emitters have earned higher risk-adjusted returns than Big Value light emitters, alongside a declining ICCs, implying that climate concerns alone cannot account for the recent disappearance of the value premium, as Growth has outperformed Value even when emissions exposure is held constant.

It is worth highlighting that our study focuses on heavy emitter firms, particularly those that fall into the Value portfolio. We leave to future and concurrent research the question of whether truly green firms (in the sense of offering climate-saving technology and being positively exposed to transition changes) command a different cost of capital.

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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 (except for Beta). Total emissions is the absolute value of each firm's Scope 1 greenhouse gas emissions in million metric tons of carbon dioxide equivalent (MmtCO$_2$e), and Carbon Intensity is each firm's Scope 1 emissions in metric tons divided by its total revenue in \$ million (mtCO$_2$e/\$M) – divided by 100 for expositional convenience. 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 %). 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, calculated as the average of the firm-level betas obtained by regressing individual stock returns on the market factor over the sample period. $t-$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
E score	-1.486	0.186	-1.673	-22.457	-1.624	0.308	-1.932	-20.447
E score coverage, %	79.87	71.13	8.70	5.450	81.79	70.52	7.00	1.340
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	1.209	1.168	0.041	1.255	1.165	1.119	0.046	1.102

Table 2: Heavy emitters share of Fama-French Book-to-Market portfolios

This table presents market capitalization share of heavy emitters in Fama-French Book-to-Market 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 in the top decile substituted for the five internal combustion engine manufacturers). The portfolio sorting procedure follows Fama and French (1993, 2015). HML portfolios are formed by first sorting on size and then sorting on the book-to-market ratio into three groups (Long, Neutral, and Short). Portfolios are re-balanced annually. The table reports the market-capitalization 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 to 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 conditional sample mean ($\bar{w}_v^k$, where k = Small or Big), are reported. For example, in the case of Small Value portfolio in the main sample the t-test compares the share to 8% (i.e., the conditional mean for Small stocks in Internet Appendix Table A.1). 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.

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)	(12.69)	(13.24)

Table 3: Heavy emitters share of Value-Growth-type characteristic-sorted 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 and growth 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. The table reports statistics for portfolios formed on the following characteristics: (i) book to market using December market equity from Fama and French (1992); (ii) tangibility from Hahn and Lee (2009); (iii) intangible return (using cash flow to price) from Daniel and Titman (2006); (iv) cash productivity from Chandrashekar and Rao (2009); (v) sales-to-price ratio from Barbee et al. (1996); (vi) operating cash flow to price from Desai et al. (2004); and (vii) cash flow to market value from Lakonishok et al. (1994). 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
Book to market using December ME	Fama & French (1992)	Low to high	2016–2023	0.02	0.09	0.21	0.29	0.36	-	-	-	-	-	0.34
				(-51.19)	(-2.40)	(7.23)	(8.57)	(10.17)	-	-	-	-	-	(14.34)
			2005–2023	0.04	0.12	0.23	0.28	0.28	-	-	-	-	-	0.24
				(-18.61)	(-2.18)	(5.28)	(7.75)	(4.93)	-	-	-	-	-	(7.34)
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)
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)
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)
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)

Table 3: Heavy emitters share of Value-Growth-type anomaly portfolios (continued)

The table reports statistics for portfolios formed on the following characteristics: (viii) enterprise multiple from Loughran and Wellman (2011); (ix) earning-to-price ratio from Basu (1977); (x) earnings-forecast-to-price from Elgers et al. (2001); (xi) long-term EPS forecast from La Porta (1996); (xii) implied equity duration from Dechow et al. (2004); (xiii) predicted dividend yield in the next month from Litzenberger and Ramaswamy (1979); and (xiv) employment growth from Belo et al. (2014). 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
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)
Earnings-to-price ratio	Basu (1977)	Low to high	2016–2023	0.15	0.15	0.19	0.19	0.26	-	-	-	-	-	0.12
				(-1.17)	(-1.38)	(0.45)	(0.61)	(2.40)	-	-	-	-	-	(2.11)
			2005–2023	0.16	0.13	0.16	0.21	0.31	-	-	-	-	-	0.15
				(-2.11)	(-4.99)	(-2.00)	(1.25)	(4.84)	-	-	-	-	-	(4.80)
Earnings forecast to price	Elgers et al. (2001)	Low to high	2016–2023	0.04	0.03	0.06	0.07	0.38	0.39	0.08	0.06	0.04	0.20	0.16
				(-13.58)	(-28.25)	(-11.62)	(-9.13)	(0.92)	(1.15)	(-15.31)	(-11.02)	(-34.68)	(-1.30)	(2.42)
			2005–2023	0.03	0.03	0.06	0.09	0.24	0.30	0.15	0.13	0.10	0.13	0.11
				(-23.12)	(-34.91)	(-12.56)	(-3.49)	(0.33)	(1.32)	(-2.04)	(-3.75)	(-4.66)	(-3.00)	(3.61)
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)
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)
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)
Employment growth	Belo 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 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 in the top decile 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), and divided by 100 for expositional convenience. 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

This table presents linear regressions of value-weighted portfolio realized and risk-adjusted returns. Panel A presents the results for the difference between the Big Value heavy-emitter and Big Value light-emitter portfolios, and Panel B presents the results for the difference between the Big Value light-emitter and Big Growth light-emitter 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 in the top decile 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. MKT, CMA, and RMW are the Fama-French factors. Columns (1)–(4) consider the 2012–2020 sample period like in Pástor et al. (2022). Columns (5)–(8) consider the 2012–2023 sample period, and Columns (9)–(12) consider the full 2006–2023 sample period. Columns (4), (8), and (12) report specifications that exclude the year 2020 (Covid period). 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 2006 to December 2023.

Panel A: Big Value heavy − Big Value light

	2012–2020				**2012–2023**				**2006–2023**			
				no 2020				no 2020				no 2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	−7.57*	−12.64***	−11.97**	−9.43*	0.06	−2.15	−3.80	−1.48	3.82	3.32	0.76	2.54
	(−1.69)	(−2.70)	(−2.32)	(−1.65)	(0.01)	(−0.30)	(−0.62)	(−0.23)	(0.72)	(0.61)	(0.16)	(0.53)
MKT		0.33***	0.38***	0.13		0.17*	0.26***	0.07		0.05	0.11	−0.02
		(2.86)	(3.37)	(0.92)		(1.70)	(2.74)	(0.71)		(0.69)	(1.47)	(−0.19)
CMA			0.80***	0.83***			0.89***	0.87***			0.58***	0.56***
			(2.62)	(2.61)			(4.70)	(4.64)			(3.23)	(3.16)
RMW			0.29	0.01			0.04	−0.09			0.35*	0.20
			(0.94)	(0.04)			(0.21)	(−0.42)			(1.85)	(1.08)
Observations	108	108	108	96	144	144	144	132	210	210	210	198
R-squared	0.00	0.07	0.14	0.07	0.00	0.02	0.16	0.15	0.00	0.00	0.07	0.06

Panel B: Big Value light − Big Growth light

	2012–2020				**2012–2023**				**2006–2023**			
				no 2020				no 2020				no 2020
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Constant	−3.92	−8.75*	−8.02**	−3.87*	−2.76	−5.04	−4.97*	−1.96	−4.09	−7.16**	−5.64***	−3.92**
	(−0.82)	(−1.86)	(−2.30)	(−1.69)	(−0.71)	(−1.06)	(−1.75)	(−0.83)	(−1.38)	(−2.34)	(−2.64)	(−2.16)
MKT		0.32***	0.37***	0.30***		0.17**	0.27***	0.20***		0.32***	0.33***	0.31***
		(4.23)	(5.48)	(4.02)		(2.23)	(3.89)	(2.63)		(5.25)	(6.01)	(5.32)
CMA			0.84***	0.92***			0.94***	0.94***			0.91***	0.92***
			(4.39)	(5.38)			(7.04)	(7.32)			(7.58)	(7.80)
RMW			−0.78***	−0.78***			−0.55***	−0.56***			−0.55***	−0.55***
			(−4.33)	(−4.65)			(−3.80)	(−3.93)			(−4.21)	(−4.27)
Observations	108	108	108	96	144	144	144	132	210	210	210	198
R-squared	0.00	0.13	0.34	0.37	0.00	0.03	0.30	0.32	0.00	0.12	0.34	0.35

Table 6: Big Value and Big Growth implied cost of capital

This table presents linear regressions of ICC differences on time period dummies. Post Paris (> 2015) is a dummy variable equal to one from July 2015 until the end of the sample, and zero otherwise. To further partition this period, we define three mutually exclusive sub-period dummies: Paris–COVID equals one from July 2015 to December 2019; COVID equals one from January 2020 to June 2020; and Post COVID equals one from July 2020 onward. In Panels (a) and (b), portfolio ICCs are computed as equal-weighted and value-weighted averages of monthly ICCs of stocks within each portfolio, respectively. 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 in the top decile 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. (2026). 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 ICC data is monthly, and the series runs from July 2006 to December 2022.

Panel A: ICC (equal-weighted portfolio)

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.27	0.03	0.03	2.65***	1.93***	1.93***
	(1.18)	(0.09)	(0.10)	(7.38)	(5.71)	(10.97)
Post Paris (>2015)		0.54			1.57***	
		(1.26)			(3.21)	
Paris–COVID			0.78*			0.81***
			(1.74)			(2.73)
COVID			−1.44			3.95***
			(−1.55)			(6.39)
Post COVID			0.51			2.50***
			(0.91)			(6.80)
Observations	198	198	198	198	198	198

Panel B: ICC (value-weighted portfolio)

	Big Value heavy − Big Value light			**Big Value light − Big Growth light**		
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	−0.11	−0.67*	−0.67**	2.97***	2.43***	2.43***
	(−0.36)	(−1.92)	(−2.01)	(10.93)	(8.17)	(13.42)
Post Paris (>2015)		1.21**			1.16***	
		(2.38)			(2.69)	
Paris–COVID			1.39**			0.52*
			(2.48)			(1.71)
COVID			0.30			2.78***
			(0.26)			(4.54)
Post COVID			1.07			2.01***
			(1.54)			(5.34)
Observations	198	198	198	198	198	198

Table 7: Big Value and Big Growth option-implied expected returns

This table presents linear regressions of the Martin and Wagner (2019) option-implied expected return lower bounds differences on time period dummies. Post Paris (> 2015) is a dummy variable equal to one from July 2015 until the end of the sample, and zero otherwise. To further partition this period, we define three mutually exclusive sub-period dummies: Paris–COVID equals one from July 2015 to December 2019; COVID equals one from January 2020 to June 2020; and Post COVID equals one from July 2020 onward. In Panels (a) and (b), portfolio option-implied expected return lower bounds are computed as equal-weighted and value-weighted averages of monthly option-implied expected return lower bounds of stocks within each portfolio, respectively. In both panels, Columns (1)-(4) present the results for the difference between the Big Value heavy emitters and Big Value light emitters portfolios, while Columns (5)-(9) 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 in the top decile 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. 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 option-implied expected return data is monthly, and the series runs from July 2006 to February 2023.

Panel A: Option-implied expected return lower bound (equal-weighted portfolio)

	Big Value heavy − Big Value light				**Big Value light − Big Growth light**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.63	−1.56	0.47	0.47	3.67***	3.76**	1.49*	1.49*
	(0.46)	(−1.03)	(0.51)	(0.56)	(2.85)	(2.20)	(1.86)	(1.79)
Post Paris (>2015)		4.77**	2.74**			−0.21	2.06*	
		(2.15)	(2.11)			(−0.09)	(1.82)	
Paris–COVID				2.76**				0.12
				(2.01)				(0.09)
COVID				10.81***				13.03***
				(3.93)				(4.41)
Post COVID				1.19				3.26**
				(0.73)				(2.00)
2008 crisis			−12.22***	−12.22***			13.62***	13.62***
			(−5.71)	(−6.38)			(7.09)	(6.72)
Observations	200	200	200	200	200	200	200	200

Panel B: Option-implied expected return lower bound (value-weighted portfolio)

	Big Value heavy − Big Value light				**Big Value light − Big Growth light**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Constant	0.08	−2.17	0.06	0.06	2.84**	4.17***	1.77*	1.77*
	(0.06)	(−1.40)	(0.06)	(0.07)	(2.08)	(2.86)	(1.70)	(1.81)
Post Paris (>2015)		4.89**	2.66*			−2.89	−0.50	
		(2.15)	(1.78)			(−1.36)	(−0.34)	
Paris–COVID				1.47				−1.27
				(1.11)				(−0.80)
COVID				15.94***				6.30*
				(5.09)				(1.76)
Post COVID				2.19				−0.46
				(1.37)				(−0.24)
2008 crisis			−13.36***	−13.36***			14.39***	14.39***
			(−5.10)	(−6.54)			(5.67)	(5.99)
Observations	200	200	200	200	200	200	200	200

Table 8: Heavy emitters share of FF portfolios (investment, profitability, and momentum)

This table presents market capitalization share of heavy emitters in Fama-French investment (CMA), operating profitability (RMW), and momentum (WML) factor portfolios. The data are annual and the main sample period is from 2016 to 2023. See Table 2 for the full table description.

Panel A: 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 B: 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 8: Heavy emitters share of FF portfolios (continued)

Panel C: 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)

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), and divided by 100 for expositional convenience. Scope 1 measures only direct emissions from production. The box encapsulates the interquartile range, with the median indicated in green. Plots' whiskers delineate the 2.5% and 97.5% percentiles. For the Utilities (Utils) and Mining (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), Transportation (Trans), Construction (Cnstr), and Hotels and Entertainment (HotEnt). Agriculture (Ag) is separated out of NoDur and presented separately. The five largest technology firms, denoted as FAAMG (Facebook/Meta, Amazon, Apple, Microsoft, and Google/Alphabet), and Berkshire Hathaway (denoted as BRK) are presented separately (details of the industry classification are provided in Section 3). The reported figures are averages across the sample period. The data are annual and the sample period is from 2016 to 2023.

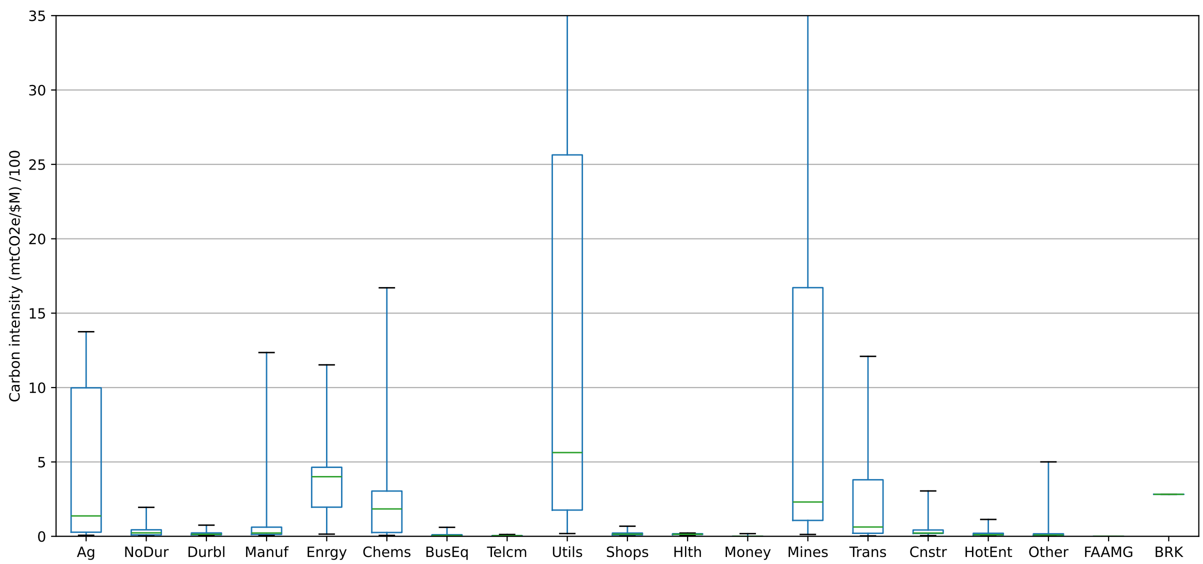
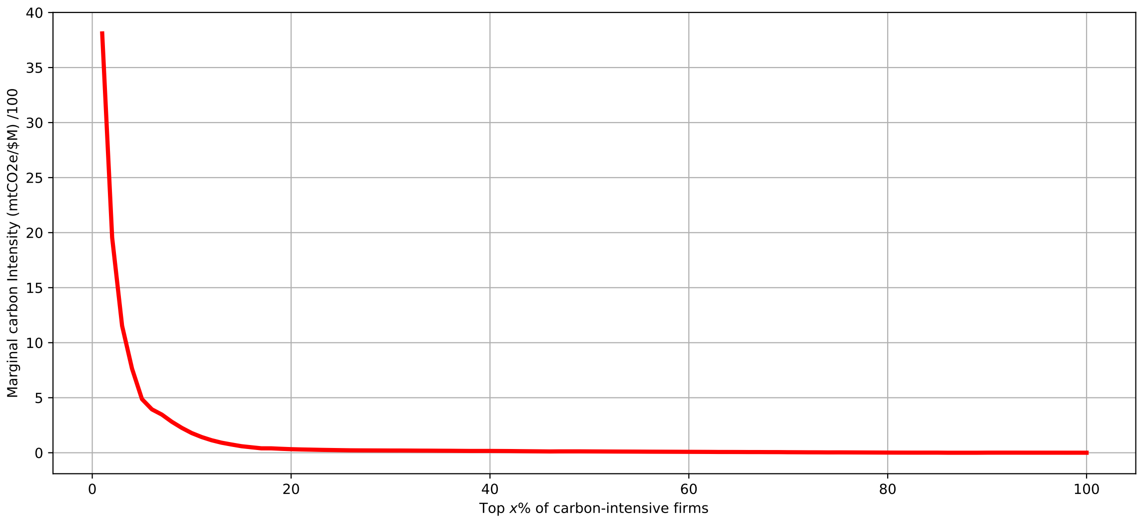


Figure 2: Marginal carbon intensity

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), and divided by 100 for expositional convenience. 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)

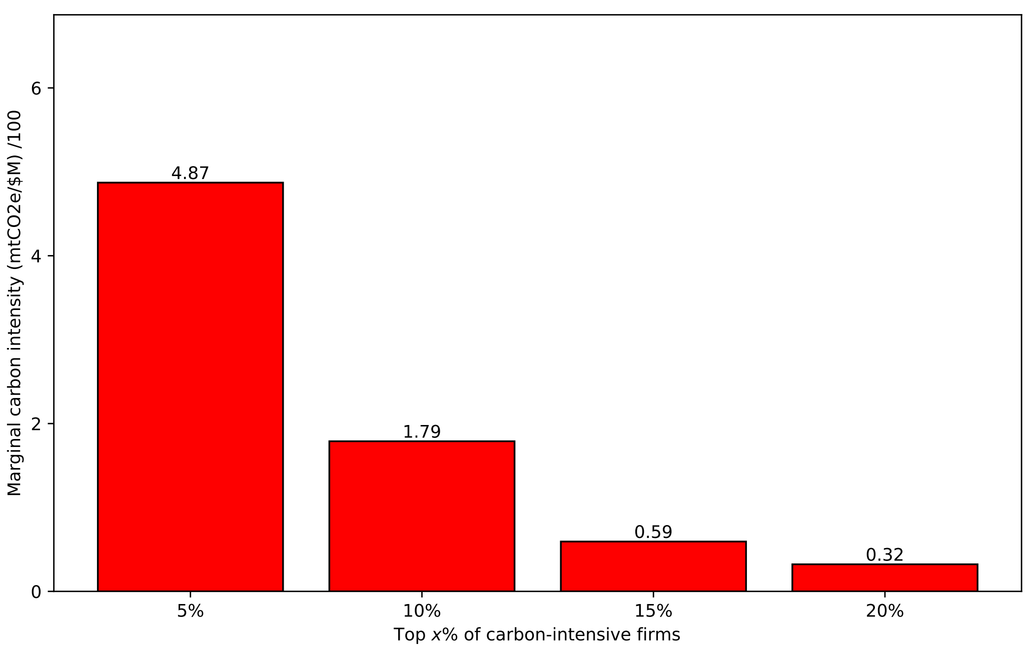
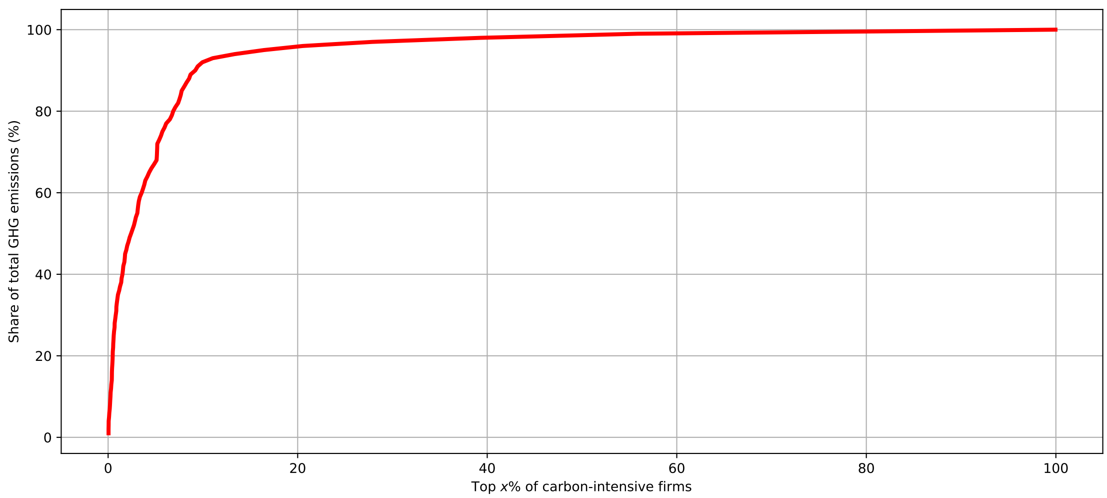


Figure 3: Contribution to aggregate GHG emissions

This shows the percentage of total GHG emissions from U.S. 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)

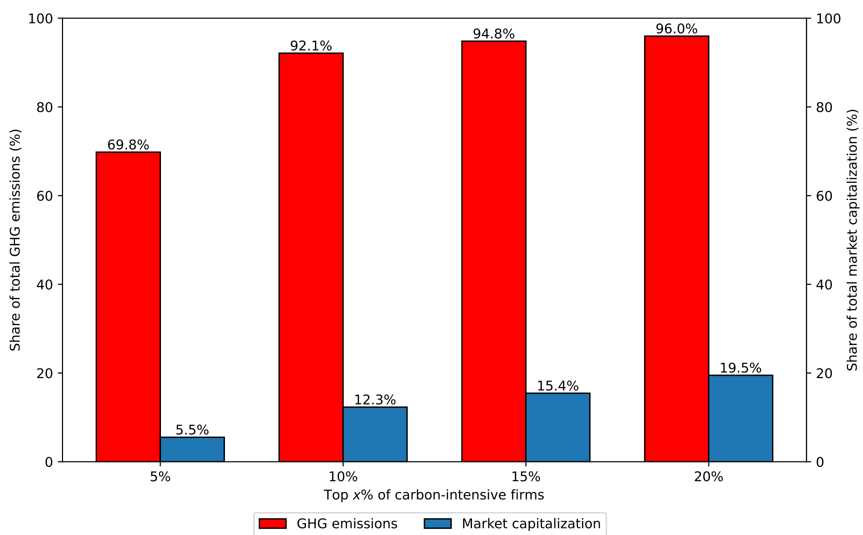
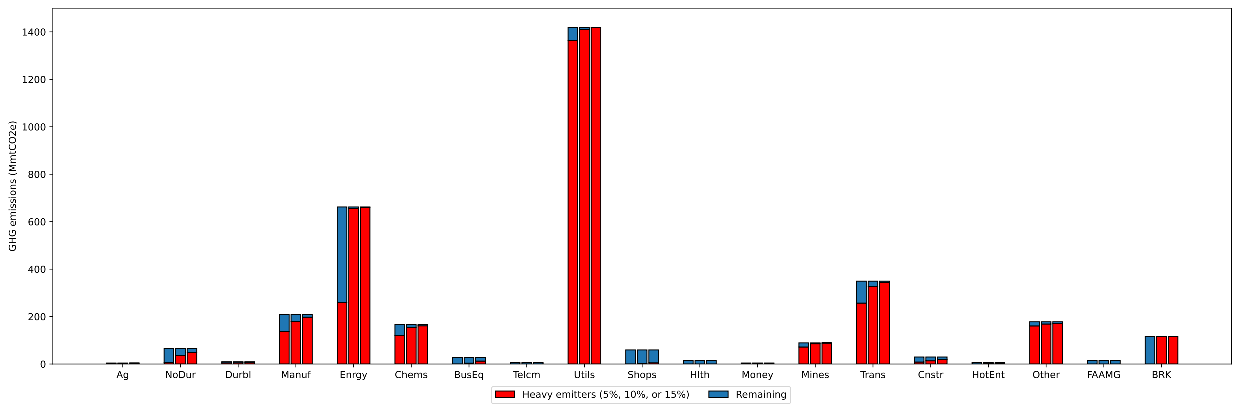


Figure 4: Emissions and market capitalization of heavy emitters by industry

This figure shows (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

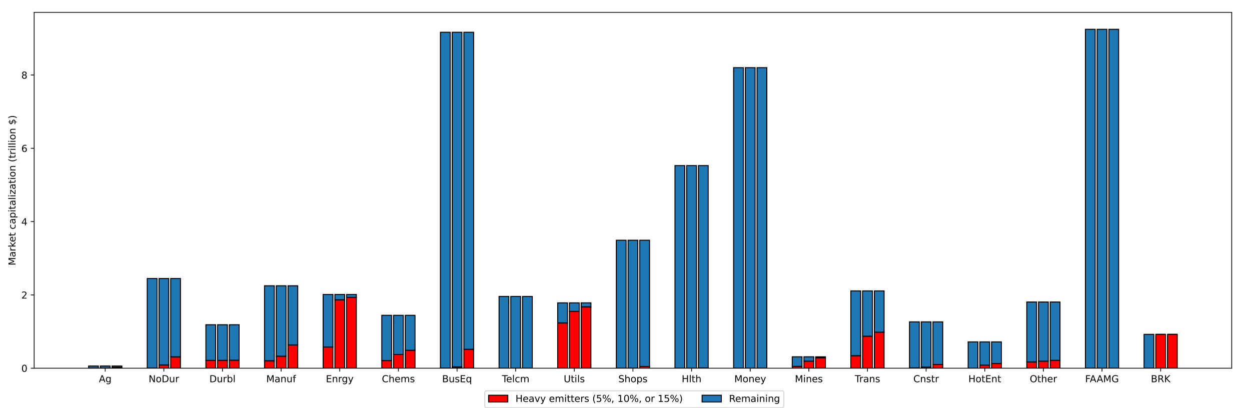
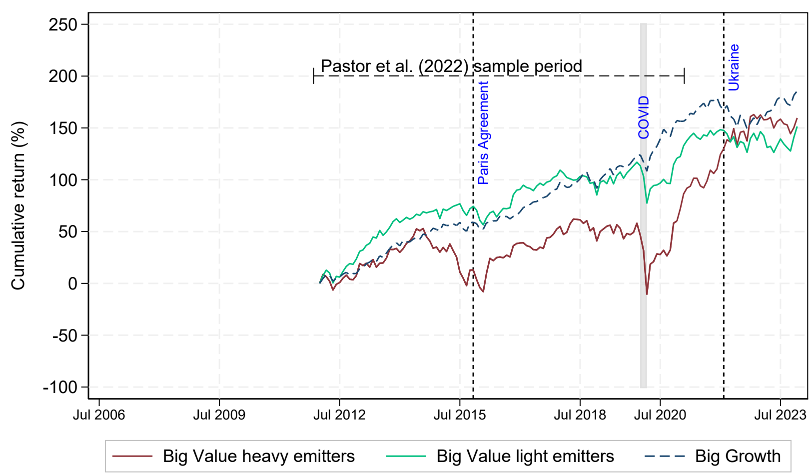


Figure 5: Realized returns of heavy and light emitters of the Big Value portfolio

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 in the top decile 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) plots the cumulative returns over the period 2012–2023 highlighting the period (2012–2020) covered by Pástor et al. (2022), and Panel (b) plots the cumulative returns over the full sample period. 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 2006 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 2012–2023



(b) Big Value performance

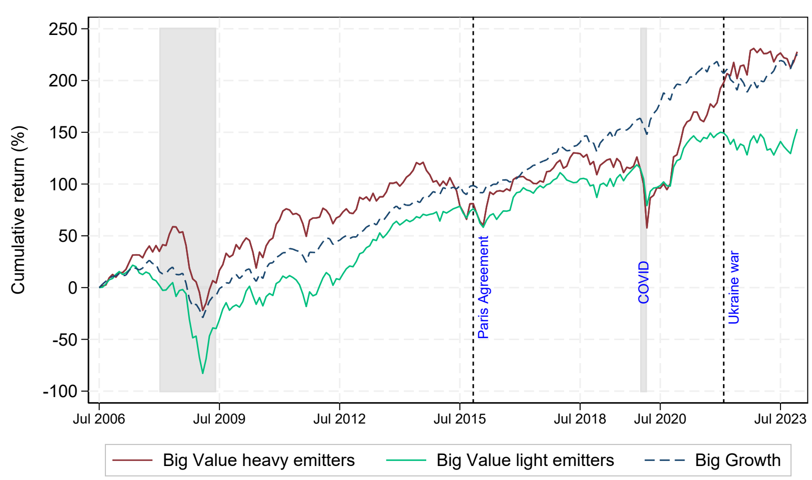
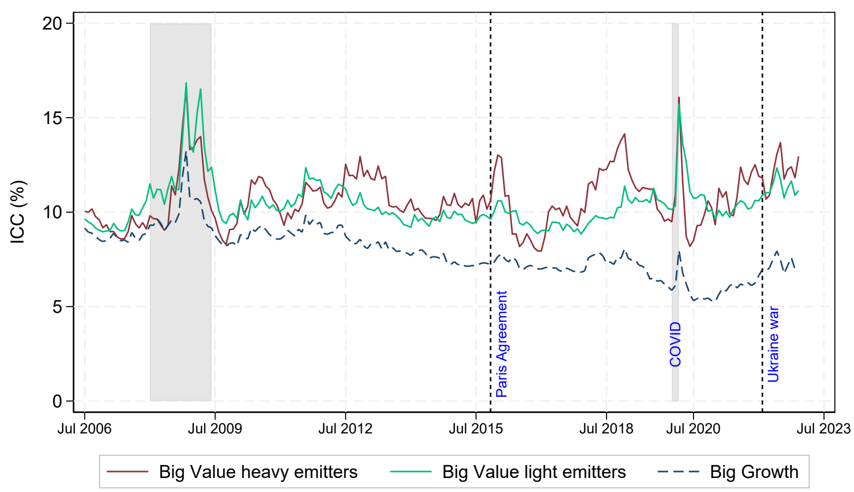


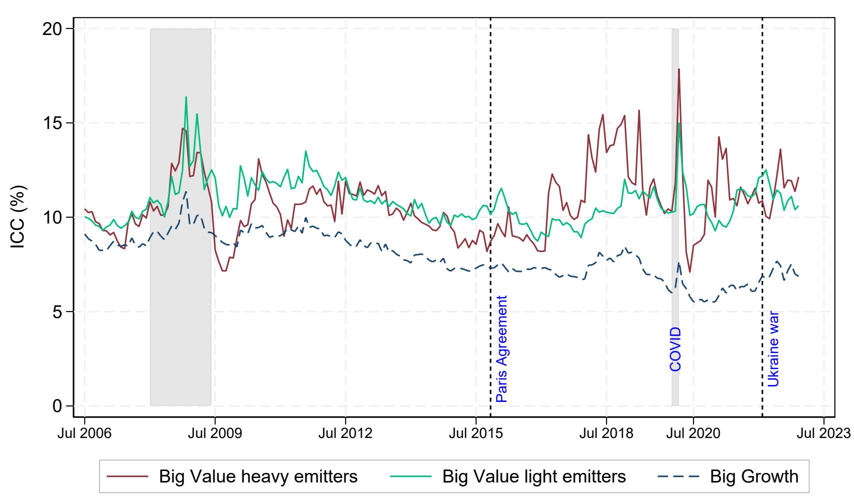
Figure 6: Implied costs of capital

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 in the top decile 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. (2026). In Panels (a) and (b), portfolio ICCs are computed as equal-weighted and value-weighted averages of monthly ICCs of stocks within each portfolio, respectively. The shaded areas denote 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 2006 to December 2022.

(a) Equal-weighted portfolios



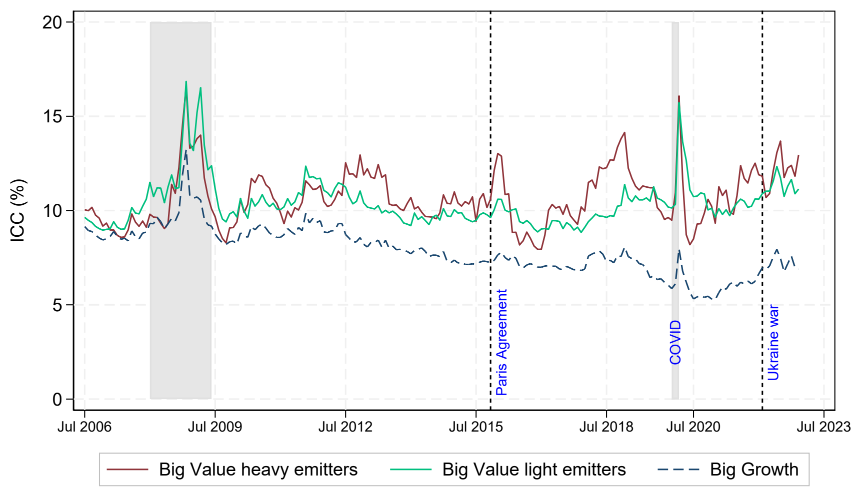
(b) Value-weighted portfolios



Implied costs of capital (no back-filled data)

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 figure corresponds to Figure 6 in the paper. Panel (a) reproduces Figure 6(a), Panel (b), however, uses a different sample. In the sample of panel (b) we define heavy emitters only using the available emissions data at each point in time (with no back-filling). In other words, firms with missing emissions data are excluded from the sample. This makes little difference post 2016, but could affect the sample composition in prior years.

(a) Equal-weighted portfolios



(b) Equal-weighted portfolios (no backfilled data)

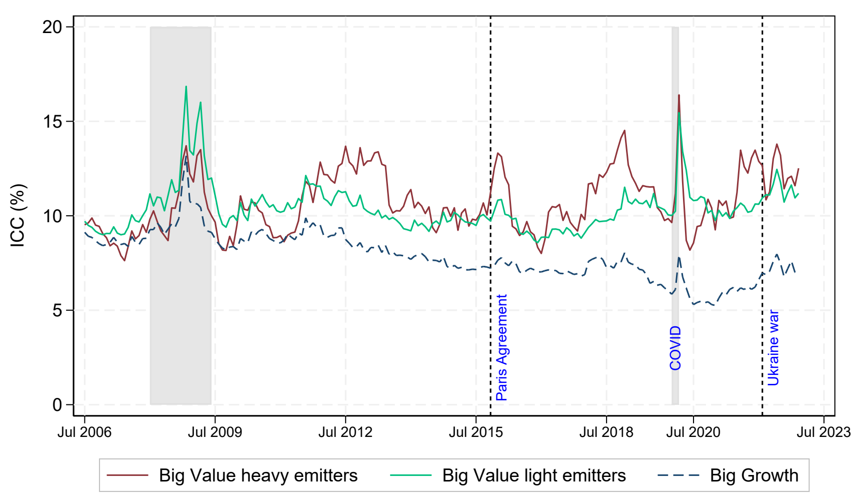
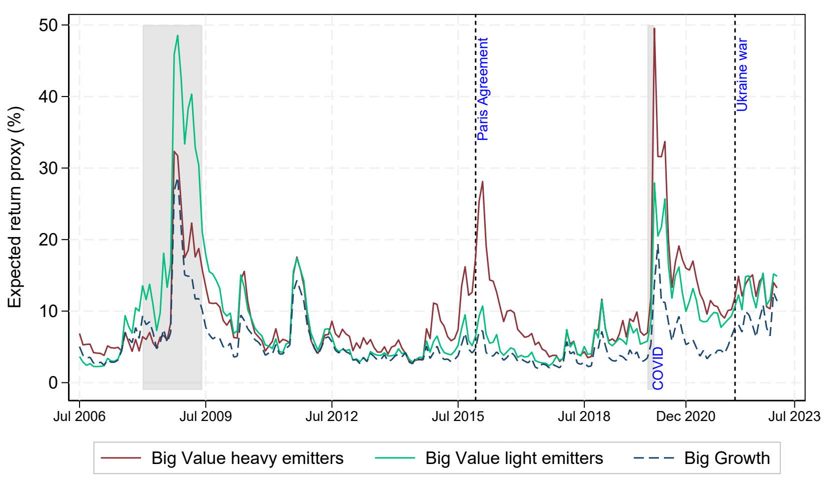


Figure 8: Option-implied expected returns

This figure shows the Martin and Wagner (2019) option-implied expected return lower bounds 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 in the top decile 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. Portfolio option-implied expected returns are computed as value-weighted averages of monthly option-implied expected return proxies of stocks within each portfolio. The shaded areas denote NBER recessions. The vertical dashed line denotes the Paris climate meeting in December 2015 and the start of the Ukraine war in February 2022. To improve visibility, extreme values around the 2008 financial crisis and the COVID period are truncated. The sample period runs from July 2006 to February 2023.

(a) Equal-weighted portfolios



(b) Value-weighted portfolios

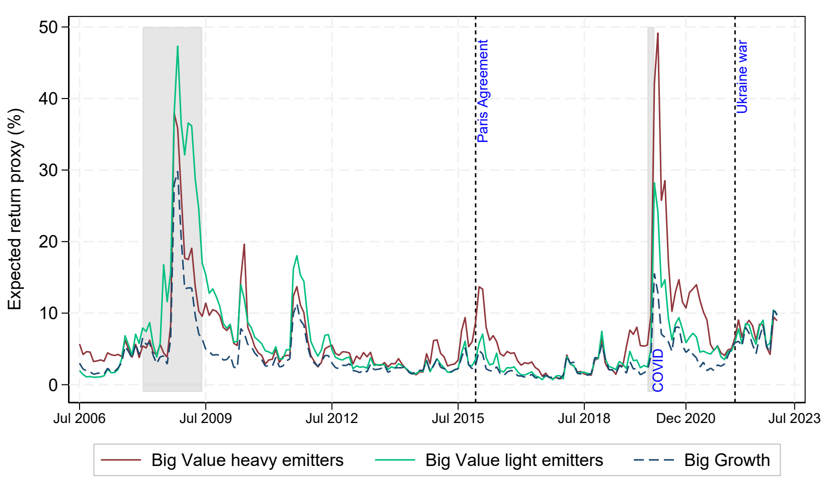
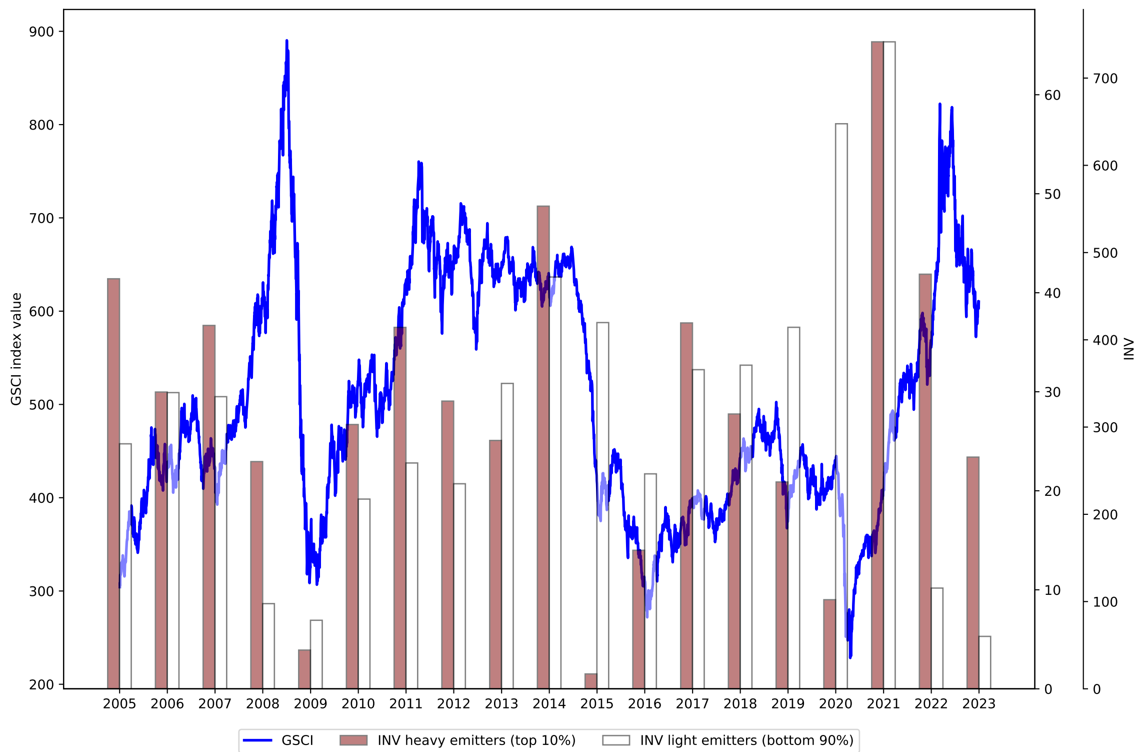


Figure 9: Heavy emitters' investments vs commodity prices

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.



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.

A 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^{th} and 70^{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.[80]

B ICC construction

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

[80] 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 Growth and Big Growth), 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.

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. (2026), 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.[81] 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 10-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.

C 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.[82] 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,

[81] 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.

[82] 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.

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.

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.

D Aggregate GHG emissions

In this subsection, we put the aggregate emissions of the firms in 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.[83] According to the U.S. Environmental Protection Agency (EPA), total U.S. GHG emissions were 6,343.2 MmtCO_2e in 2022. Hence, 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.

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

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%.[84] 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).[85] 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, about 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).[86] Real estate investment trusts (REITs) cover less than 10% of the commercial real estate market (Nareit, 2021), and real-estate ETFs are small, primarily investing in REITs.[87] 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-

[84]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).

[85]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).

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

[87]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).

owned commercial real estate.[88] 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.[89]

E 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 84 firms in the CRSP sample and with emissions data in Trucost, 81% 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 seven of the 11 industries are classified as heavy emitters. The Internet Appendix provides the coverage details. Specifically, as noted in our earlier analysis,

[88] 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.

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

our basic approach does not initially classify automobile manufacturers as heavy emitters. We add internal combustion engine automobile manufacturers to our final list of heavy emitters and thus include 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.[90] The only utility company not included in the list of heavy emitters is Eversource Energy. As noted above, the company transitioned to renewable energy sources and substantially reduced its carbon footprint, and therefore no longer classified as a heavy emitter during the 2016–2023 period. 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 three firms among the Food Producers as heavy emitters, but not the other eleven, which include General Mills, Kraft Heinz, or Tyson Foods. However, given their relatively low carbon intensity and diversified product offerings, these food companies are arguably not as severely exposed to transition risk, making their omission from the list of heavy emitters justifiable.

[90] 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.

Table A.1: Heavy emitters share of Fama-French Size portfolios

This table presents market capitalization share of heavy emitters in Fama-French Size 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 in the top decile substituted for the five internal combustion engine manufacturers). The portfolio sorting procedure follows Fama and French (1993, 2015). Two size portfolios are formed by sorting stocks into two buckets on size (Small and Big) using the NYSE median as the cutoff. Portfolios are re-balanced annually. Each panel of the table reports the market-capitalization 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 to 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 are reported. For the difference between Long and Short shares and the 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.

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 A.2: 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.2: 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)

	Small	Big	Small	Big	Small	Big	Small	Big	
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)

	Small	Big	Small	Big	Small	Big	Small	Big	
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.2: 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**		**Short** *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.3: Pollution and Size across Big Value and Big Growth Portfolios

This table presents summary statistics for the number of stocks, total market capitalization, and total absolute pollution across low- and high-emitting firms within the Fama-French Big Value and Big Growth 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. The figures are means and medians over the period 2016 to 2023, based on annual data.

	Big Value		**Big Growth**	
	Light emitter	Heavy emitter	Light emitter	Heavy emitter
Number of stocks	104	40	409	23
Total value (market cap, trillion)	2.20	1.18	18.31	0.71
Total absolute pollution (mil. m. tons CO_2e)	15.4	583.7	65.7	167.8

Table A.4: Fundamental Characteristics across Big Value and Big Growth Portfolios

This table presents firm characteristics summary statistics for low- and high-emitting firms within the Fama-French Big Value and Big Growth 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 in the top decile substituted for the five internal combustion engine manufacturers), while light emitters are firms that do not fall into this category. Utility firms are excluded when computing the statistics. BM is the firm's book to market ratio. INV is investments scaled by total book assets. OP is operating profits scaled by book equity. Beta refers to the CAPM beta, computed using a full-sample period time series regression. BM, INV, and OP are winsorized at the 2.5% levels. $t-$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). Statistics are computed over the period 2006–2023, based on annual data sampled in July of each calendar year.

				Difference	
	Big Value heavy	Big Value light	Big Growth light	BV heavy − BV light	BV light − BG light
Panel A: Means					
log(Size)	9.26	8.95	9.50	0.31*	−0.55***
				(1.66)	(−4.86)
BM	0.96	1.15	0.22	−0.20***	0.93***
				(−3.27)	(16.75)
INV	0.04	0.05	0.18	−0.01	−0.12***
				(−0.47)	(−6.12)
OP	0.16	0.16	0.35	0.00	−0.19***
				(0.06)	(−5.87)
Beta	1.23	1.22	1.06	0.00	0.16***
				(0.02)	(3.04)
Panel B: Medians					
log(Size)	9.11	8.69	9.22	0.42*	−0.53***
				(1.76)	(−4.02)
BM	0.87	1.00	0.19	−0.13***	0.81***
				(−3.54)	(28.45)
INV	0.02	0.02	0.07	−0.00	−0.05***
				(−0.25)	(−8.71)
OP	0.18	0.16	0.36	0.02	−0.20***
				(1.16)	(−15.66)
Beta	1.23	1.21	1.04	0.02	0.17***
				(0.20)	(3.20)

Table A.5: 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 in the top decile 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.6: Heavy emitters share of other characteristics-sorted portfolios

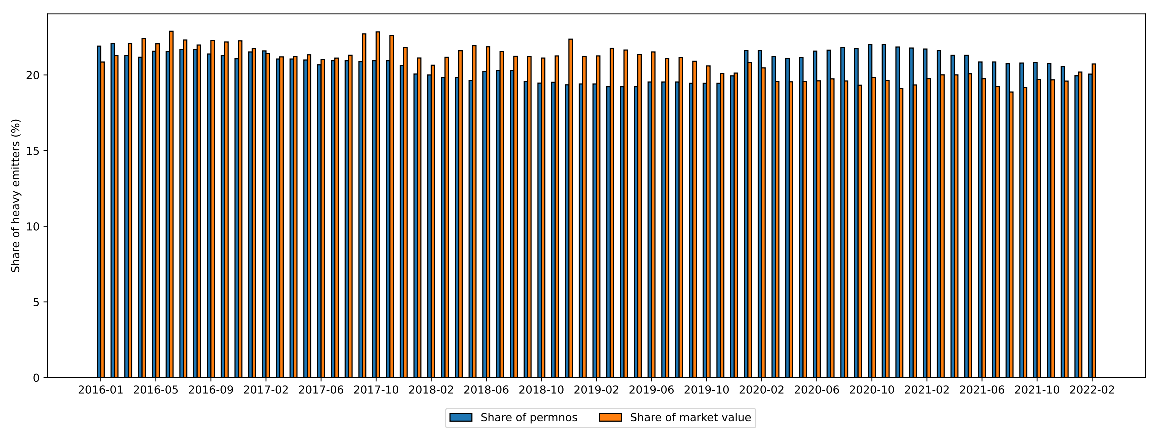
This table presents market capitalization share of heavy emitters in characteristic-sorted anomaly portfolios from Chen and Zimmermann (2021). Detailed table description can be found in Table 3. The anomalies considered are: (i) cash holdings from Palazzo (2012); (ii) earnings consistency from Alwathainani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

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 in the top decile 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)

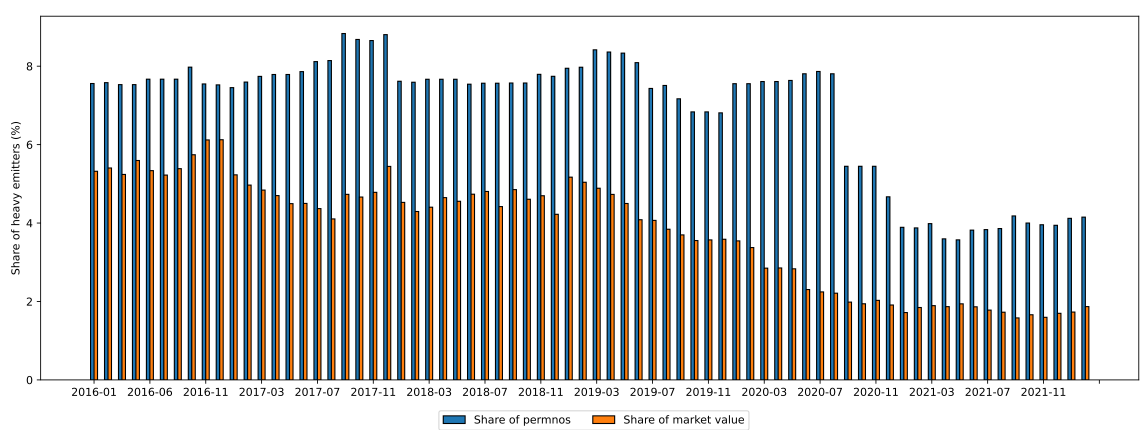
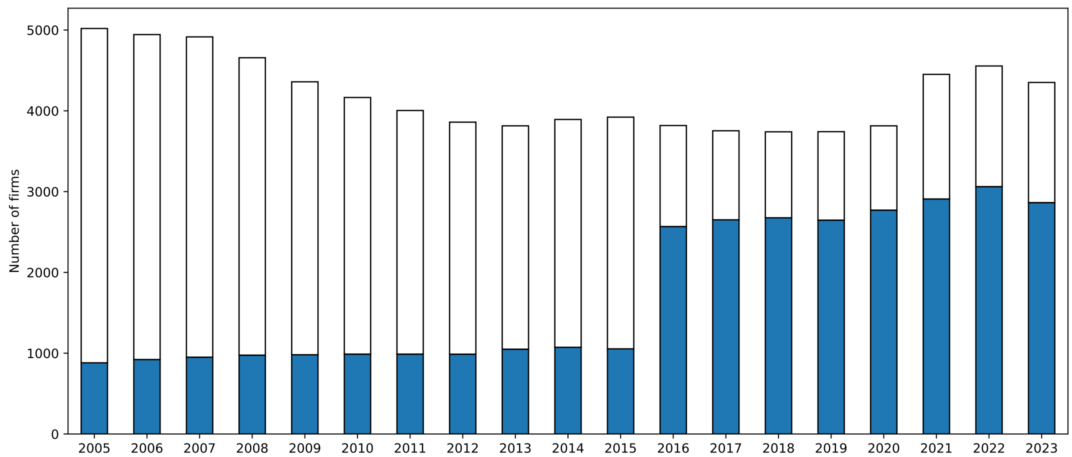


Figure A.2: Greenhouse gas emissions data coverage

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 U.S. 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

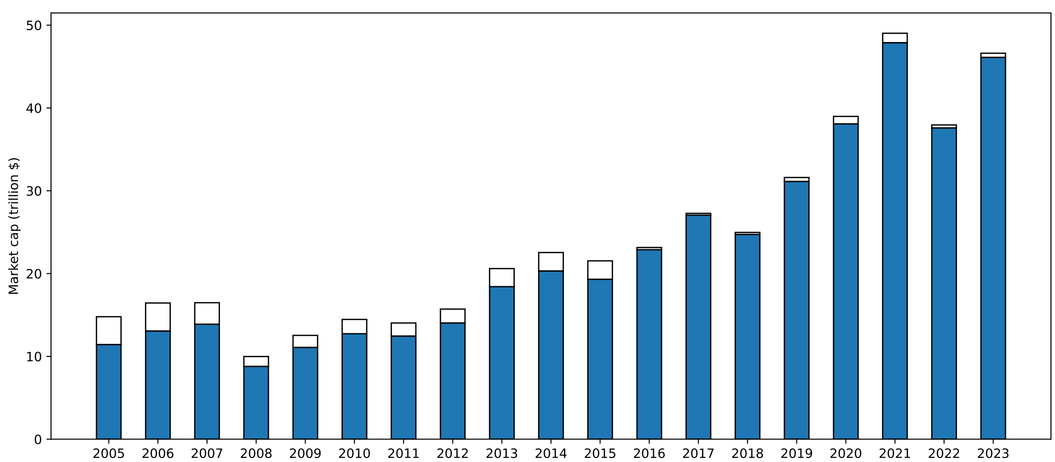
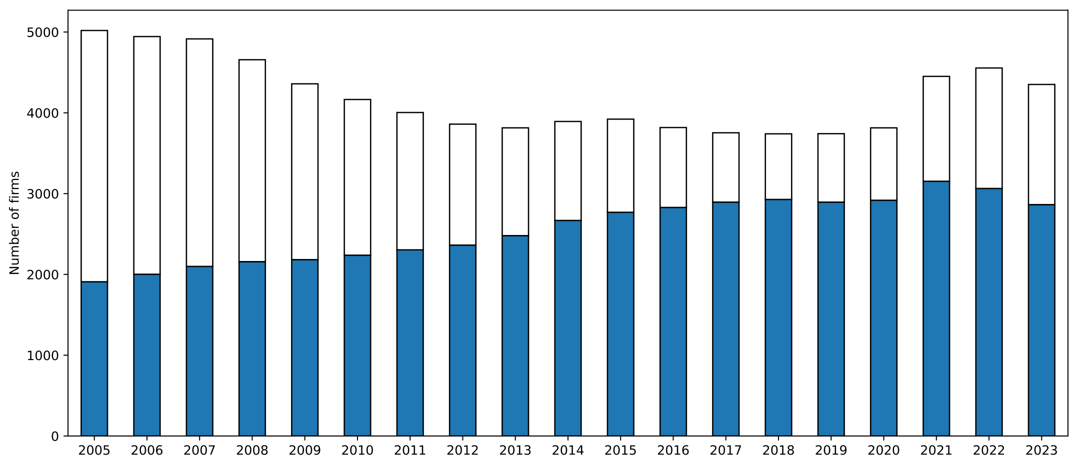


Figure A.3: Greenhouse gas emissions data coverage (back-filled data)

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 U.S. 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

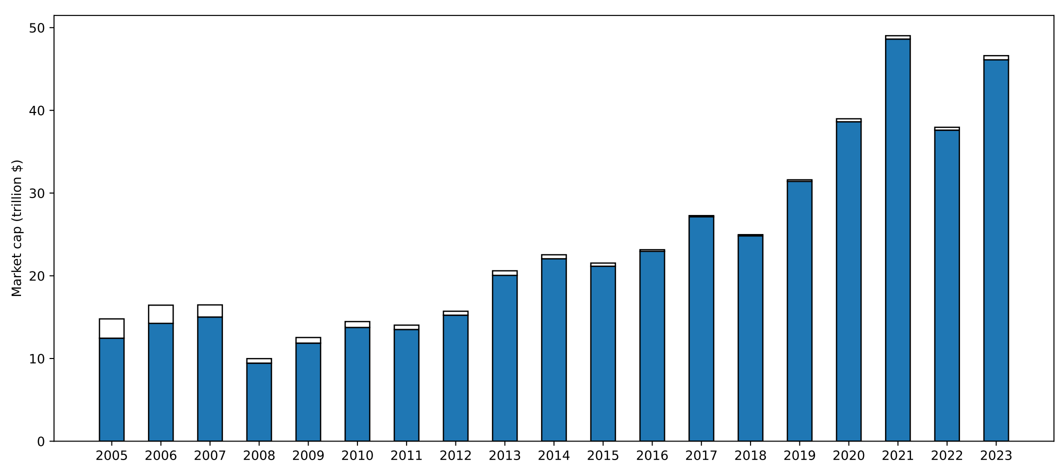
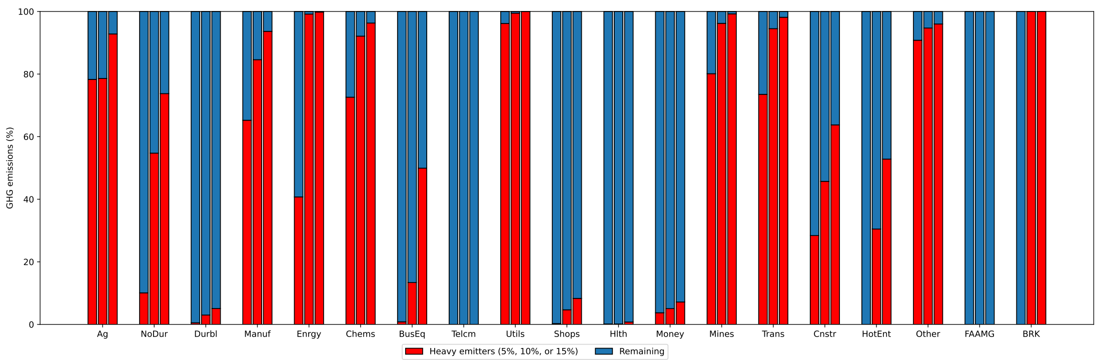


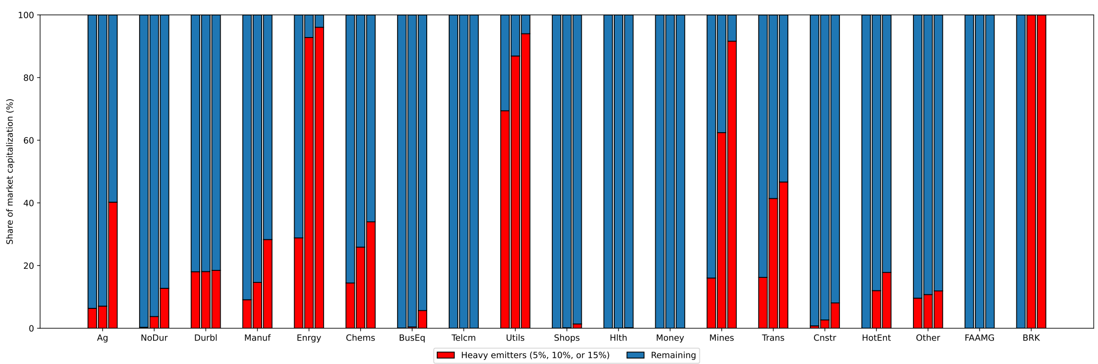
Figure A.4: Emissions and market capitalization of heavy emitters (share of total)

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 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



(c) Number of firms

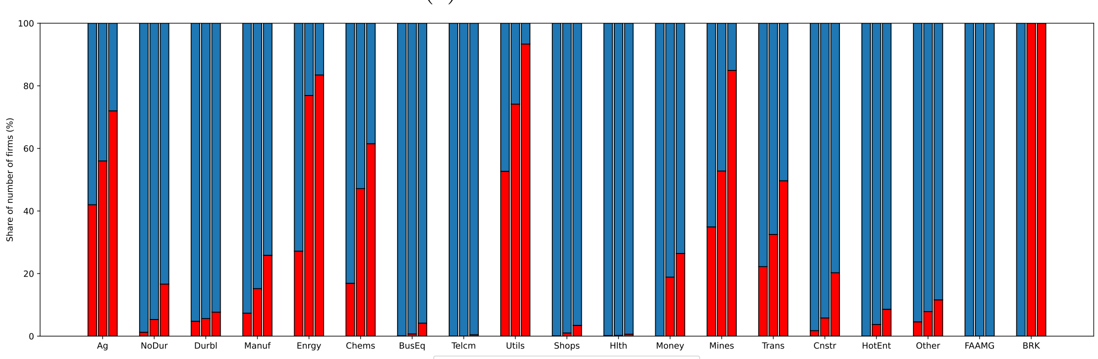
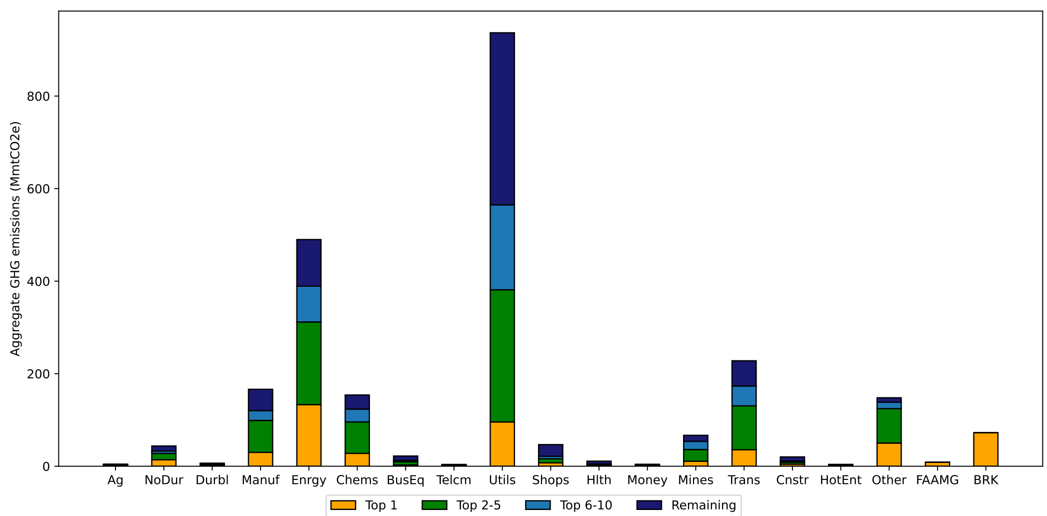


Figure A.5: Distribution of aggregate GHG emissions and market capitalization by industry

Panel (a) of this figure shows the total Scope 1 GHG emissions among publicly-traded U.S. 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

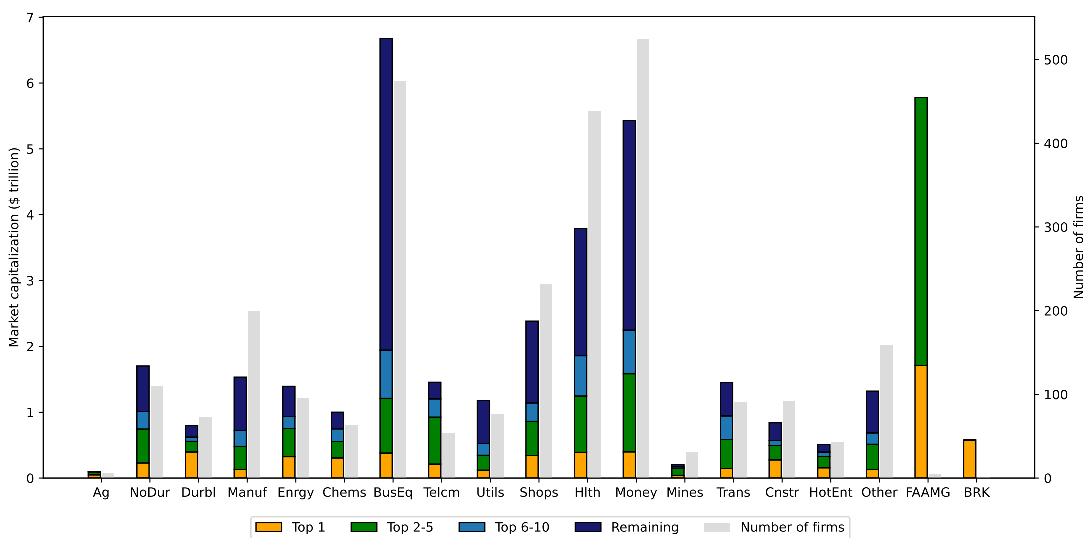
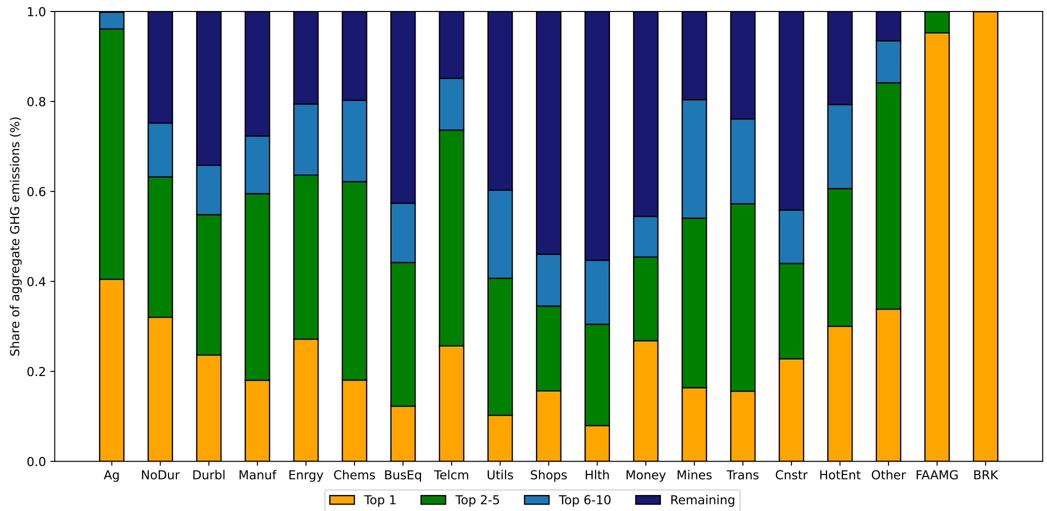


Figure A.6: Aggregate emissions and market capitalization by industry (share of total)

Panel (a) of this figure shows the relative share of top firms of the total GHG emissions among publicly-traded U.S. 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

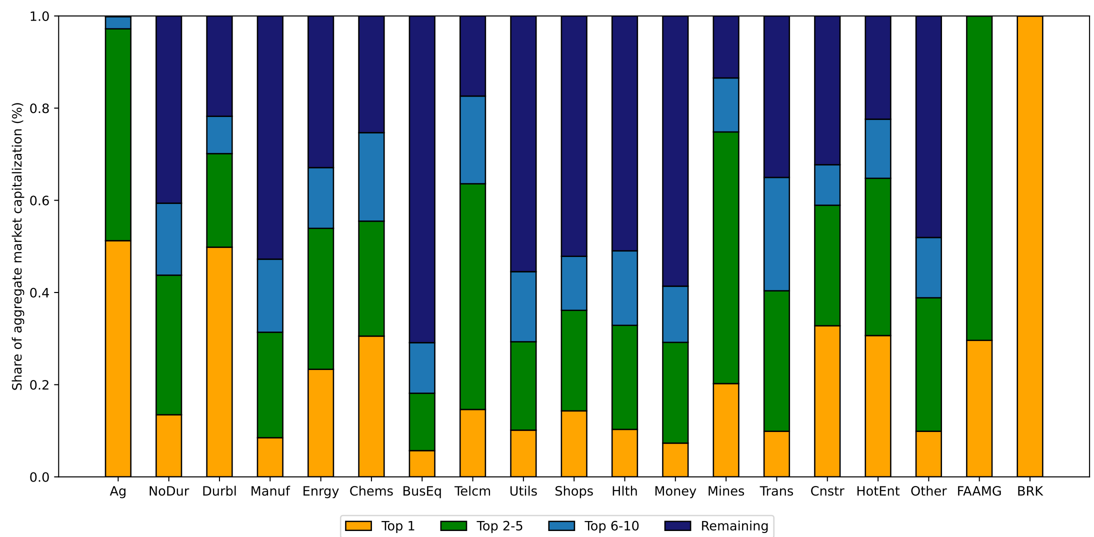


Figure A.7: Persistence of carbon-intensity rankings

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 i, given a ranking of decile j in the previous year.

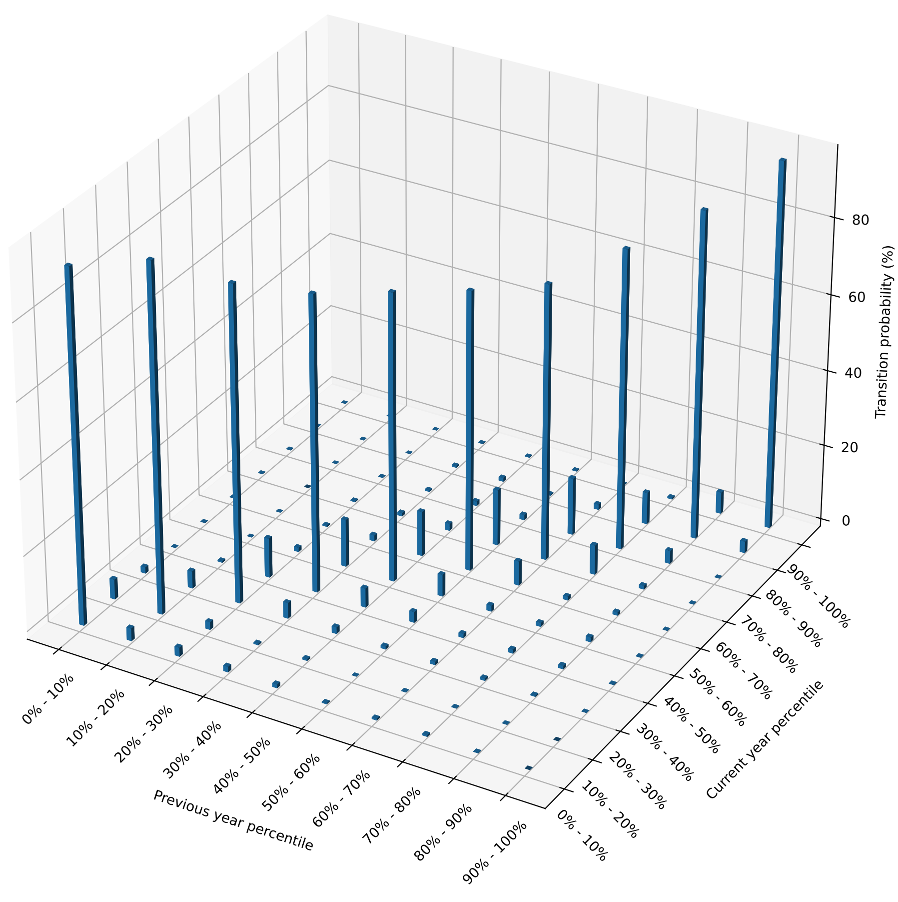


Figure A.8: Carbon-intensity rankings and E scores

This figure shows a 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.

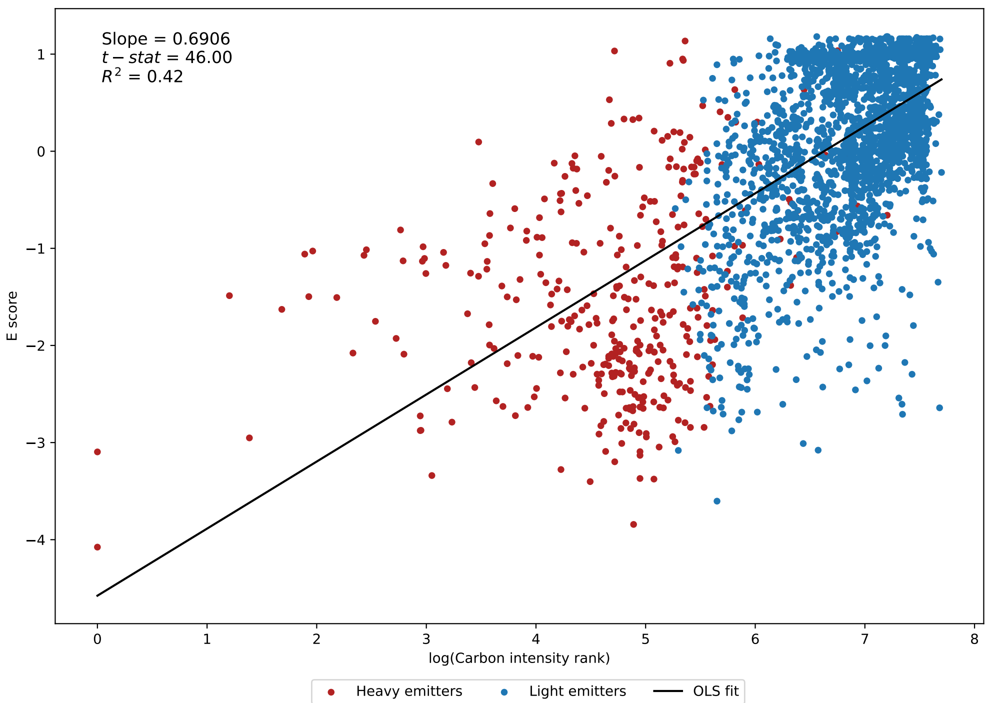


Figure A.9: Intersection of heavy emitters and firms covered by TPI Centre

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 five least carbon intensive firms substituted for the five 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

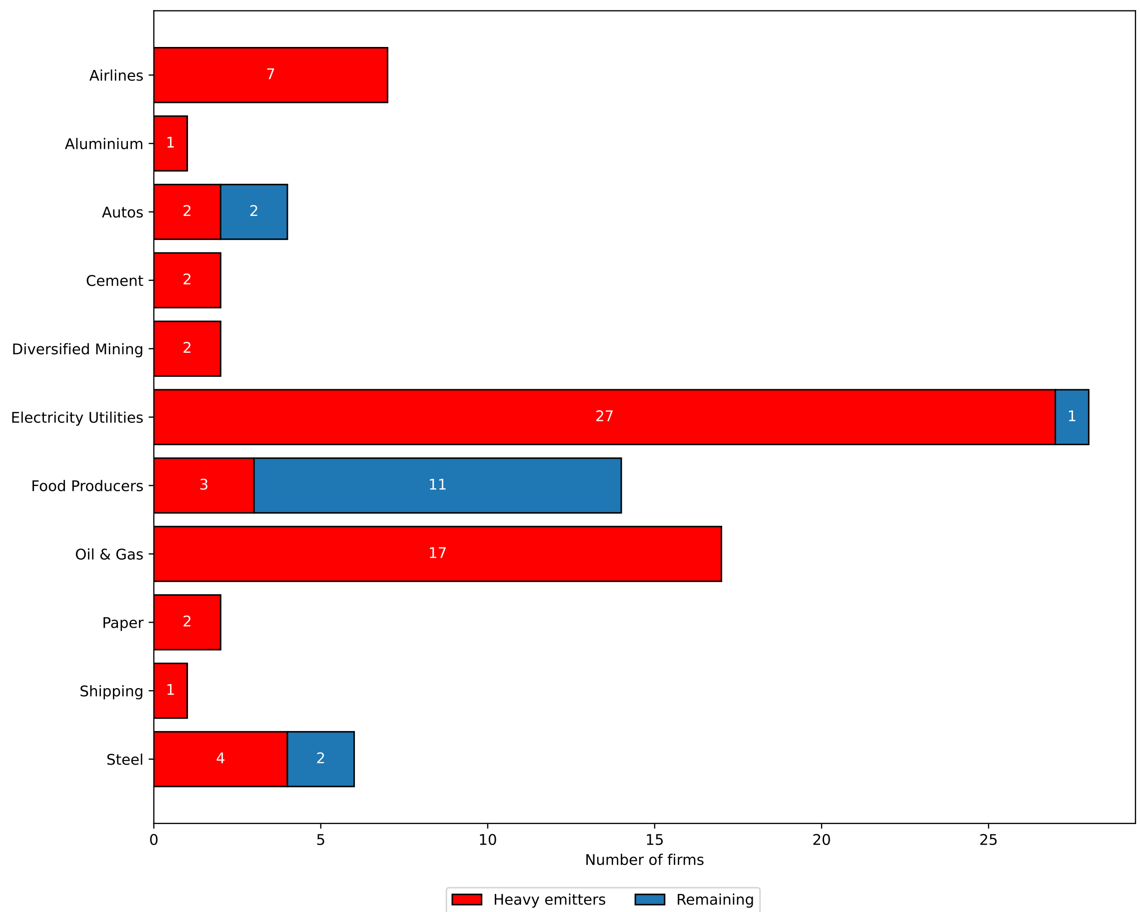


Figure A.10: Aggregate GHG emissions

This figure shows the aggregate Scope 1 GHG emissions among publicly-traded U.S. 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.

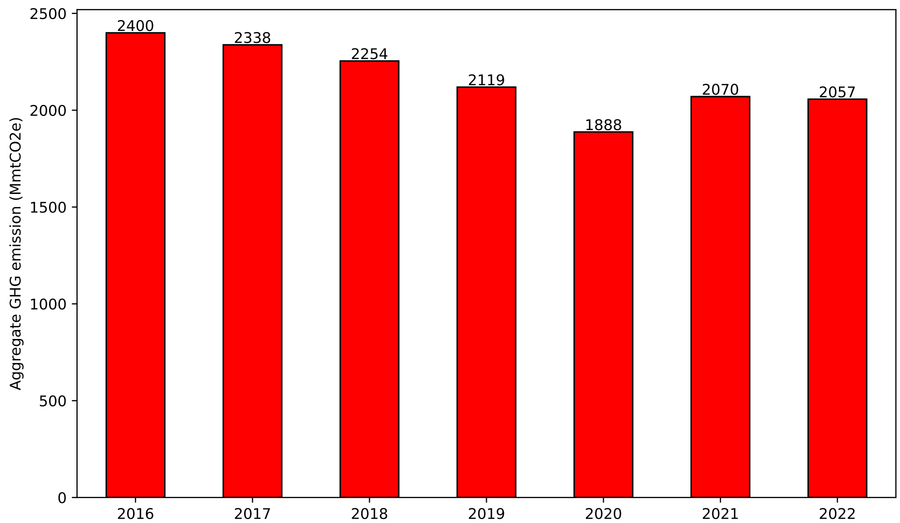
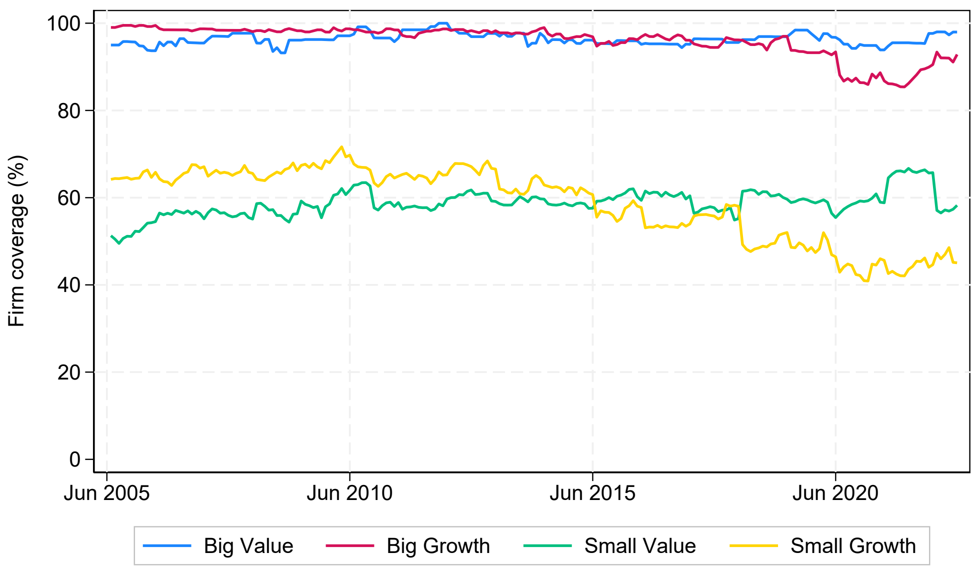


Figure A.11: ICC coverage

This figure shows the coverage of the 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

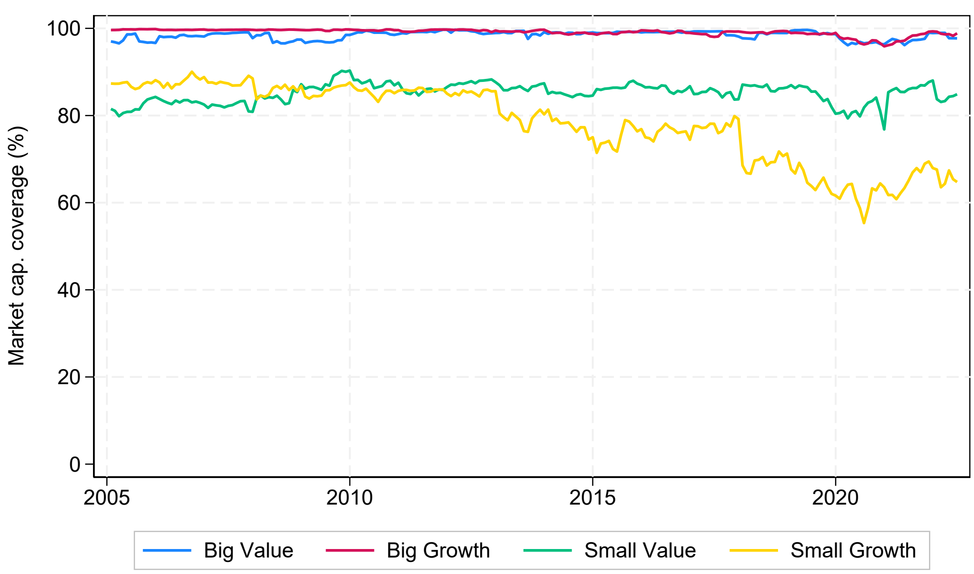
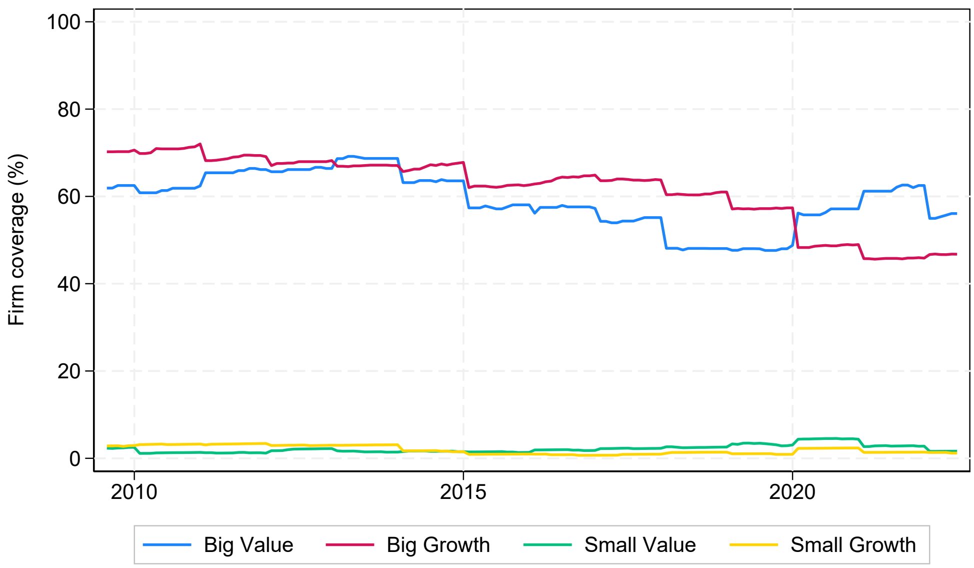


Figure A.12: Option-implied expected return lower bounds coverage

This figure shows the coverage of the option-implied Martin and Wagner (2019) expected return lower bounds 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). The sample period runs from January 2010 to December 2022.

(a) Firm coverage



(b) Market capitalization coverage

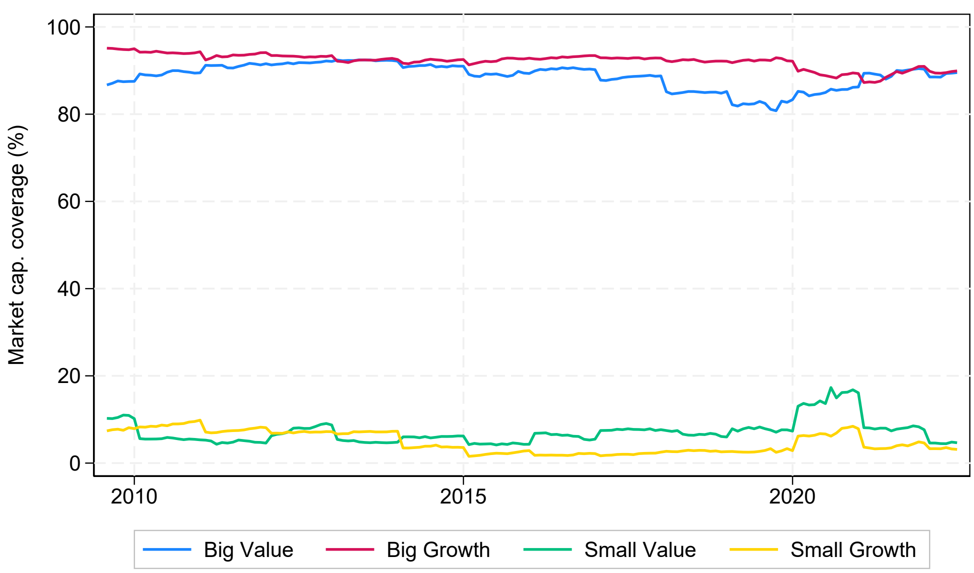


Figure A.13: Big Value heavy and light emitter return spread

This figure 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 2006 to December 2023 (in the years prior to 2016, backfilled emissions data are used to identify heavy emitters when no data is available).