Carbon tilts and factor returns[*]

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Abstract

Carbon transition risk is increasingly reflected in asset prices and is central to the sustainability debate. We study how carbon risk affects the cross-section of expected U.S. equity factor returns using carbon tilts, defined as the value-weighted difference in carbon transition risk between a factor's long and short legs. While carbon-intensive factors earn lower realized returns, forward-looking expected returns based on the implied cost of capital indicate a positive carbon tilt premium that increases with unanticipated climate concerns and over time. Carbon risk varies across investment styles and is most pronounced for strategies linked to profitability, investment, and valuation.

Keywords: Carbon tilts, factor returns, climate finance, transition risk, investment styles

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1. Introduction

Climate change is among the most urgent challenges facing the global community, and curbing carbon emissions is increasingly critical to keeping global warming within the 1.5–2.0°C range set out in the Paris Agreement. Achieving this target requires a rapid transition from fossil fuels to renewable energy sources to become carbon-neutral by 2050. In response, governments, banks, and institutional investors have increasingly committed to net-zero targets, putting growing pressure on high-emitting firms to reduce their carbon footprints and exposing them to transition risk (Bolton and Kacperczyk, 2021, 2023).[1] How carbon transition risk is priced and impacts the financial landscape is a central question in climate finance, especially as asset managers and investors increasingly incorporate sustainable and carbon neutrality objectives into their portfolio decisions.[2]

This paper addresses these questions and offers a new perspective on the pricing of carbon risk. Specifically, we study how carbon risk is reflected in the expected returns of 160 long-short U.S. equity factors from 2010 to 2022. Our main variable of interest is the *carbon tilt* of a portfolio, defined as the difference in carbon risk between the factor's long and short legs. We proxy carbon risk using Scope 1 and Scope 1+2 total emissions and emissions scaled by sales (emission intensity). The basic premise of our analysis is that factors tilted toward carbon-intensive firms should display higher expected returns as compensation for carbon transition risk exposure. Yet, the same factors may have underperformed in realized returns if investors have gradually decarbonized their portfolios and reallocated capital away from heavy-emitting firms. For example, the carbon-intensive nature of value stocks can explain the poor performance of value strategies during the

[1]Examples include the European Green Deal, which outlines a roadmap for Europe to become climate-neutral by 2050, the Net Zero Asset Managers initiative (https://www.netzeroassetmanagers.org/, and the UN-supported Principles for Responsible Investment (PRI) (https://www.unepfi.org/net-zero-alliance/).

[2]For example, Starks (2023) shows that U.S. active mutual funds increased their ownership of sustainable firms between 2013 and 2021. Investors increasingly demand sustainable and low-carbon assets (Hartzmark and Sussman, 2019, Ceccarelli, Ramelli, and Wagner, 2024, Emiris, Harris, and Koulischer, 2024) and institutional investors underweight firms with large carbon footprints (Nofsinger, Sulaeman, and Varma, 2019, Bolton and Kacperczyk, 2021, Bolton, Eskildsen, and Kacperczyk, 2025). The reduction in carbon exposure is facilitated by institutions joining climate-friendly initiatives and increasing their holdings of firms with low carbon emissions (Gibson Brandon, Glossner, Krueger, Matos, and Steffen, 2022, Atta-Darkua, Glossner, Krueger, and Matos, 2023) and the growing popularity of net-zero portfolios (Bolton, Kacperczyk, and Samama, 2022, Cenedese, Han, and Kacperczyk, 2024).

recent decade (Pástor, Stambaugh, and Taylor, 2022). We focus on equity factors for four main reasons. First, a factor-level analysis allows us tocrixet explore how carbon risk shapes the broader investment landscape and menu of investment styles. Second, it provides insight into how firm-level carbon risk influences factor and style performances. Third, analyzing different categories of factors can uncover variation across investment styles and shed light on potential exposure heterogeneity originating from their underlying selection criteria (e.g., value factors may overweight carbon-intensive firms). Fourth, factors are well-diversified portfolios, which help mitigate firm-specific noise.

We examine the impact of carbon tilts on U.S. equity factors by estimating the carbon tilt premium as the slope coefficient in a pooled cross-sectional regression of factor returns on carbon tilts. The carbon tilt premium measures the annualized expected return differential between high-emitting ("brown") factors and low-emitting ("green") factors per standard deviation increase in carbon tilts. We begin by investigating realized factor returns and observe a negative carbon tilt premium across all carbon risk proxies. This suggests that factors tilted towards high-carbon firms have underperformed compared to low-carbon firms. Although this finding appears puzzling from a theoretical standpoint, as brown firms should have higher expected returns due to their high transitional risk (Pástor, Stambaugh, and Taylor, 2021, Hsu, Li, and Tsou, 2023), our findings are consistent with the negative carbon premium documented by Zhang (2025). We view the negative carbon tilt premium for realized returns to reflect an ongoing transition to a low-carbon equilibrium, wherein investors gradually decarbonize their portfolios by divesting from high-emitting firms (Pástor et al., 2022, Cenedese et al., 2024).

We then turn to forward-looking expected returns, which have recently been shown to provide more accurate carbon premia estimates (Pástor et al., 2022, Sautner, van Lent, Vilkov, and Zhang, 2023b, Eskildsen, Ibert, Jensen, and Pedersen, 2024). Our main measure is the implied cost of capital (ICC), which infers expected returns by combining market prices with analysts' forecasted cash flows using standard discounted cash flow models. We find that ICC carbon tilt premia are positive across all carbon measures, with notably larger magnitudes, stronger significance, and greater explanatory power for emission intensity. These results are consistent with theoretical predictions that carbon-intensive assets should carry higher expected returns (Pástor et al., 2021). Collectively, our baseline results reveal a negative carbon premium in realized returns but a positive and significant carbon premium in forward-looking ICC returns, particularly pronounced when focusing on emission intensity.

Next, we examine how carbon tilt premia respond to climate-related shocks and evolve over our sample period. To capture unanticipated shifts in climate concerns, we use the media climate change concern index (MCCC) from Ardia, Bluteau, Boudt, and Inghelbrecht (2023) and measure shocks as prediction errors from an ARX-based model. We then interact these shocks with carbon tilts in our regressions. We find that the carbon tilt premium for realized returns increases during periods of unexpectedly high climate concerns, even turning positive during large shocks, supporting the view that the underperformance of carbon-tilted factors largely reflects transitional effects. Similarly, the ICC carbon tilt premium also increases significantly in response to climate shocks, indicating that investors demand higher compensation for carbon-intensive strategies when climate concerns spike unexpectedly. To assess the time-series evolution of carbon tilt premia, we (i) estimate baseline slope coefficients using rolling-window regressions and (ii) interact carbon tilts with a linear time trend. The carbon premium for realized returns declines over most of the sample but rises toward the end. More notably, ICC carbon tilt premia steadily increase throughout our sample period, consistent with a gradual repricing of carbon risk as the economy transitions toward a low-carbon equilibrium.

The second part of the paper examines heterogeneity in carbon tilt premia across investment styles. We classify factors into eight groups: earnings, frictions, intangibles, investment, momentum, profitability, risk, and valuation. The benchmark negative carbon tilt premium for realized returns is concentrated among earnings, intangibles, profitability, and valuation factors. Conversely, the positive and economically significant ICC carbon tilt premium for emission intensity is primarily driven by investment, profitability, and valuation factors. This suggests that carbon transition risk is not uniformly priced across factors, but is instead concentrated in strategies linked to firm fundamentals such as operational efficiency, expansionary behavior, and long-term value. ICC carbon tilt premia increase in response to unanticipated climate shocks and over time during our sample period, confirming our benchmark results.

We complement our ICC-based analysis of the carbon tilt premium with option-implied measures of expected returns. Specifically, we consider the lower bound from Martin and Wagner (2019) (MW) and the generalized lower bound (GLB) from Chabi-Yo, Dim, and Vilkov (2023b). Since these measures are only available for S&P 500 firms, we limit the sample accordingly. The evidence from option-implied returns is mixed: both MW and GLB returns indicate a negative carbon premium for total emissions but a positive premium for emission intensity. Consistent with our ICC findings, MW carbon premia increase significantly over time, while GLB premia for emission intensity decline. These differences highlight the sensitivity of carbon premium estimates to the choice of transition risk proxies, expected return measures, and the role of higher-order risk-neutral moments.

The final part of the paper demonstrates the robustness of our findings across alternative specifications, estimation methods, and climate risk measures. First, we confirm that our baseline results carry through when using only reported emissions, addressing concerns about the influence of vendor-estimated emissions (Bolton and Kacperczyk, 2023, Aswani, Raghunandan, and Rajgopal, 2024). Second, we estimate carbon tilt premia using Fama and MacBeth (1973) regressions and obtain identical conclusions. Third, we aggregate our four carbon risk measures into a composite *carbon score*, following Eskildsen et al. (2024). Finally, we use an alternative firm-level proxy for climate risk from Sautner, van Lent, Vilkov, and Zhang (2023a) and find comparable pricing patterns.

Our paper contributes to a rich literature that studies the financial effects of climate change (surveyed by Hong, Karolyi, and Scheinkman (2020), Giglio, Kelly, and Stroebel (2021), Gillan, Kock, and Starks (2021), Hong and Shore (2023), and Pástor, Stambaugh, and Taylor (2024b)). Our work is most closely related to studies of carbon risk. Theoretically, we expect to find a positive carbon premium (Pástor et al., 2021, Hsu et al., 2023) as heavy-emitters face investor exclusion (Bolton et al., 2022, Cenedese et al., 2024), similar to sin stocks (Hong and Kacperczyk, 2009). Empirically, the evidence is mixed.

Bolton and Kacperczyk (2021, 2023) find a positive carbon premium when measuring carbon risk using total emissions, but not for emission intensity. Hsu et al. (2023) provide evidence of a positive pollution premium based on toxic emission intensity. Eskildsen et al. (2024) construct a "robust green score" based on multiple climate-related variables, including total emissions and emission intensities, and find a strong carbon premium that increases over time. On the other hand, Aswani et al. (2024) find no evidence of a carbon premium when restricting the analysis to firms with reported emissions only (i.e., when excluding vendor-estimated emissions). Zhang (2025) finds a negative carbon premium using emission intensity and appropriately lagging emission data to account for publication lags and the correlation of estimated emissions with firm fundamentals such as sales. A connected literature provides evidence that financial markets can facilitate decarbonization. Carbon-intensive industries reduce emissions faster in economies with deeper stock markets (De Haas and Popov, 2023), green investing pushes companies to reduce their carbon emission by raising their cost of capital (De Angelis, Tankov, and Zerbib, 2023), and institutional investors underweight companies with higher carbon emissions (Atta-Darkua et al., 2023, Bolton et al., 2025).

Our study contributes to this debate by shifting the focus from firm-level to factor-level pricing. Specifically, use portfolio carbon tilts to document a negative carbon premium in realized returns and a positive premium in ICC returns that (i) increases with climate concerns and time and (ii) varies across investment styles. These results suggest that carbon risk is increasingly reflected in expected returns, with important implications for investors seeking to align portfolios with carbon objectives. For example, Pástor, Stambaugh, and Taylor (2025) estimate the U.S. corporate sector's carbon externality to be about 131% of total corporate equity value.

More broadly, our paper also speaks to a growing body of theoretical work examining how sustainability preferences influence expected returns (Pástor et al., 2021, Pedersen, Fitzgibbons, and Pomorski, 2021, Zerbib, 2022), the link between social preferences, discount rates, and corporate policies (Oehmke and Opp, 2025, Dangl, Halling, Yu, and Zechner, 2024, Landier and Lovo, 2025, Green and Roth, 2025), and the effects of divestiture in the secondary market on firms' cost of capital (Lo and Zhang, 2024, Berk and van Binsbergen, 2025). Krueger, Sautner, and Starks (2020) finds that institutional investors find engagement more effective than divestment for addressing climate change.

Our work also relates to studies on the demand for sustainability. Mutual fund flows respond strongly to sustainability ratings (Hartzmark and Sussman, 2019) and "low-carbon" labels (Ceccarelli et al., 2024, Emiris et al., 2024). More broadly, Pástor and Vorsatz (2020) find that investor appetite for ESG investing surged during the COVID-19 pandemic but has recently cooled (Baker, Egan, and Sarkar, 2024). Yet, Pástor, Stambaugh, and Taylor (2024a) estimate that ESG tilts account for only 6% of total assets under management.

Several empirical studies examine sustainability metrics and their impact on asset prices. Pástor et al. (2022) and Pedersen et al. (2021) examines ESG scores and asset prices. Engle, Giglio, Kelly, and Stroebel (2020) develop climate risk indices and analyze their role in hedging climate risk. Faccini, Matin, and Skiadopoulos (2023) use news-based climate indices to assess whether physical and regulatory climate risks are priced in financial markets. Sautner et al. (2023a) use textual analysis on earnings calls to develop firm-level climate risk measures and Sautner et al. (2023b) study if they are priced in the cross-section of expected stock returns. Ardia et al. (2023) find that green firms outperform brown firms following unexpected increases in climate concerns, as suggested in Pástor et al. (2021). Gormsen, Huber, and Oh (2024) document that green firms have lower perceived costs of capital and discount rates than brown firms. Pedersen (2024) develops a unifying model of carbon pricing and green finance, showing that ESG investing can be effective if carbon prices are set below their social cost.

The rest of the paper proceeds as follows. Section 2 describes our data sources, the construction of realized and forward-looking factor returns, and carbon tilts. Section 3 presents our main empirical results on carbon tilts and factor returns. Section 4 studies carbon tilts across investment styles. Section 5 considers option-implied expected factor returns. Section 6 provides additional results and robustness checks on our main conclusions. Section 7 provides concluding remarks.

2. Data and variables

Our sample consists of publicly listed U.S. firms with available stock returns from CRSP and emissions and sales data from LSEG from 2010 to 2022. We first describe the firm-level return and emission data. Next, we outline the firm characteristics used to construct factor portfolios and detail the construction of carbon tilts. Finally, we describe the climate concern indices, firm-level climate risk exposure measures, and control variables used in the analysis.

2.1. Realized and forward-looking expected stock returns

This section presents our proxies for expected stock returns. Our first measure is the one-month realized return in excess of the one-month Treasury bill rate (RET). We source realized stock returns from CRSP and the one-month T-bill from Kenneth French's data library.[3] Realized excess returns are commonly used as unbiased proxies for expected returns in asset pricing tests. However, their validity can be limited in short sample periods like those typically available for studying climate-related risks and variables (Pástor et al., 2022, Sautner et al., 2023b, Eskildsen et al., 2024).

To address this concern, we consider the implied cost of capital (ICC) as an ex-ante forward-looking measure of expected returns. The ICC estimates a stock's expected return by combining current market prices with analysts' forecasted cash flows. ICC returns, which are obtained from Eskildsen et al. (2024), are computed as the equal-weighted average across four standard valuation models from the accounting literature (Gebhardt, Lee, and Swaminathan, 2001, Claus and Thomas, 2001, Easton, 2004, Ohlson and Juettner-Nauroth, 2005), following Mohanram and Gode (2013).[4] We use ICC as our main proxy for forward-looking expected returns for three reasons: it (i) tracks time-varying expected returns well empirically (Pástor, Sinha, and Swaminathan, 2008, Li, Ng, and Swaminathan, 2013), (ii) is widely used in climate finance (see, e.g., Pástor et al. (2022) and Eskildsen et al. (2024)), and (iii) has broad cross-sectional coverage across U.S. equities.

[3] The data is available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.
[4] The data are available from Theis Ingerslev Jensen's website: www.tijensen.com/data.

In supplementary analyses, we also consider option-implied proxies for forward-looking expected returns. Specifically, we use the SVIX lower bound from Martin and Wagner (2019) (MW) and the generalized lower bound (GLB) from Chabi-Yo et al. (2023b).[5] These measures capture expectations embedded in option-implied risk-neutral distributions. MW is based on the stock's option-implied risk-neutral variance and captures expected returns of a log-utility investor fully invested in equities. GLB extends this approach to higher-order moments (beyond second-order moments as in MW) by using the full risk-neutral distribution embedded in option prices, and captures expected returns under a general utility framework. The proxies are available at the daily frequency and we aggregate them to monthly observations by taking within-month averages, following Chabi-Yo et al. (2023b) and Eskildsen et al. (2024). Because MW is limited to S&P500 constituents, we similarly limit GLB to the same universe for comparability. We find, in unreported results, that GLB results are similar using the broader universe.[6] We focus on the 30-day forward-looking expected return in our analyses.

[Insert Table 1 about here]

Panel A of Table 1 presents firm-level summary statistics for the four expected return proxies. The average annualized realized excess return (RET) is 14.99%, with an annualized standard deviation of 39.96%. The distribution of realized returns is skewed, with a 25th percentile return of -53.86%, a 75th percentile return of 76.94%, and a median annualized return of 12.70%. In contrast, the implied cost of capital (ICC) returns have a lower mean (8.66%) and a significantly lower standard deviation (3.59%), consistent with the interpretation as a more stable, forward-looking measure of expected returns. The interquartile range (6.47% to 10.20%) is narrow and suggests that ICC estimates cluster around typical equity discount rates used in valuation.

The option-implied proxies for expected returns, MW and GLB, have lower means of 4.96% and 8.57%, respectively. GLB is more volatile than MW (standard deviation of

[5]The data are provided by Grigory Vilkov: doi.org/10.17605/OSF.IO/Z2486.

[6]Chabi-Yo, Dim, and Vilkov (2023a) provide GLB returns for all firms with data in OptionMetrics that can be matched to PERMNO in CRSP. We limit the sample to S&P500 constituents in our results to provide a fair and direct comparison with Martin and Wagner (2019) bounds. The empirical results for the full universe of GLB returns are not materially different from those in the S&P500 sample.

9.77% versus 6.74%) and exhibits greater dispersion across firms with a wider interquartile range (3.64 to 10.21) than MW (1.61 to 5.98). Importantly, these proxies are constructed for a smaller sample, consisting only of S&P 500 firms, and represent lower bounds on expected returns under specific assumptions about investor preferences and market structure.

2.2. Carbon emissions

Measuring transition risk exposure in factor portfolios is difficult. Our main measures are based on firm-level carbon emissions from LSEG, which provides annual data on emissions in tons of carbon dioxide equivalent (tCO2e). For readability, we scale emissions to megatons (MtCO2e) throughout the analysis. Carbon emissions are widely used as firm-level indicators of transition risk and distance to carbon neutrality (see, e.g., Bolton and Kacperczyk (2021, 2023)). To avoid look-ahead bias and ensure that emissions data reflect information available to investors at the time, we use point-in-time carbon emission disclosures as suggested by Zhang (2025). We link emissions data to CRSP and forward-looking return proxies using CUSIP and ISIN identifiers. Figure 1 illustrates the evolution of emission data coverage in LSEG for each year in our sample. The number of U.S. firms with available emissions data has grown steadily over the sample period, likely due to improved disclosure practices and growing investor attention to climate risk.

[Insert Figure 1 about here]

We focus on two commonly used measures in our empirical tests: Scope 1 and Scope 1+2 emissions. Scope 1 includes direct emissions from sources owned or controlled by the firm, e.g., company vehicles or the fossil fuel used in production. Scope 2 captures indirect emissions from the firm's electricity, heat, steam, and cooling consumption.[7] In our empirical analyses, we consider both unscaled (total) emissions and emissions scaled by sales (i.e., emission intensities). Both measures have been widely studied in the literature,

[7] The Greenhouse Gas Protocol also includes Scope 3 emissions, which are indirect emissions from the firm's upstream and downstream value chain activities that are not owned or controlled by the firm, e.g., emissions from purchased materials, outsourced activities, or business travel. We exclude the indirect Scope 3 emissions from our analysis because they are noisy and difficult to measure and assign accurately.

though their implications for expected returns differ (see, e.g., Bolton and Kacperczyk (2021, 2023), Aswani et al. (2024), and Zhang (2025)). The choice between total emissions and emission intensity is not trivial and may reflect different economic mechanisms. While total emissions reflect a firm's absolute carbon footprint and distance to carbon neutrality, which is relevant for investors concerned with aggregate decarbonization efforts (Bolton et al., 2022, Cenedese et al., 2024), they often scale linearly with firm size. Emission intensity, conversely, captures carbon efficiency relative to a firm's activities (e.g., sales), potentially making it more suitable for cross-sectional comparisons of carbon risk (Zhang, 2025). However, variations in emission intensity can originate not only from emissions, but also from fluctuations in sales. Given these nuances and mixed findings in the literature, we explore both measures and their implications for expected factor returns.

[Insert Figure 2 about here]

Panel A of Table 1 reports descriptive statistics for Scope 1 and Scope 1+2 unscaled and scaled emissions, respectively. Total emissions are highly right-skewed, driven by a few heavy emitters with substantial carbon footprints. Emission intensities are also skewed, though less so, as scaling by sales accounts for a firm's activity (Zhang, 2025). Figure 2 illustrates the evolution of average firm-level emissions and emission intensity over time. While average total emissions have declined during our sample period, emission intensity exhibits cyclical variation, with a modest increase between 2016 and 2018.

2.3. Characteristics and portfolio construction

We construct 160 long-short factor portfolios for our baseline analysis using stock-level characteristics from the Open Source Asset Pricing database of Chen and Zimmermann (2022). This database maintains a broad and standardized set of firm-level characteristics, including both classic factor such as size (Banz, 1981), value (Stattmann, 1980, Rosenberg, Reid, and Lanstein, 1985, Fama and French, 1992), and momentum (Jegadeesh and Titman, 1993), alongside more recently proposed return predictors like idiosyncratic volatility (Ang, Hodrick, Xing, and Zhang, 2006), changes in CAPEX (Andersen and Garcia-Feijóo, 2006), and patents-to-R&D expenses (Hirshleifer, Hsu, and Li, 2013). The characteristics data use a standard six-month lag for annual accounting data availability and a one-quarter lag for quarterly accounting data availability.

We focus on continuous signals that are consistently available throughout our sample period. Discrete signals are excluded as they perform poorly in standard one-way portfolio sorts, which form the core of our analysis. We also drop characteristics with poor cross-sectional coverage.[8] To assess heterogeneity across investment styles, we categorize the firm-level characteristics into eight groups: Earnings (12), Frictions (22), Intangibles (16), Investment (32), Momentum (22), Profitability (17), Risk (18), and Valuation (21). The classification scheme is inspired by the taxonomy of Hou, Xue, and Zhang (2020). The Internet Appendix provides a complete list of factor definitions and groupings.

For our main analysis, we compute monthly value-weighted long-short factor returns for each characteristic using both RET and ICC returns. Each month, we rank stocks based on their characteristic (signed so that high values predict higher returns, as in the original studies) and assign them to one of five value-weighted portfolios based on NYSE breakpoints. The factor portfolio return is defined as the excess return on a zero-investment strategy that takes a long position in the highest quintile and a short position in the lowest quintile. We also compute monthly value-weighted factors for MW and GLB returns using S&P500 firms following a similar procedure.

To assess and track the carbon exposure embedded in the factor investing strategies, we compute factor-level *carbon tilts* as the value-weighted difference in carbon transition risk between the factor's long and short legs. Carbon exposure is measured using both Scope 1 and Scope 1+2 unscaled and scaled emissions, respectively, for a total of four different transition risk proxies. These measures indicate whether a given strategy overweights high-emitting ("brown") firms or low-emitting ("green") firms. Positive values correspond to long positions in firms with larger carbon footprints or less efficient operations.

Panels B through E of Table 1 report summary statistics for factor-level returns and carbon tilts across the four expected return proxies. Panel B shows that realized factor

[8]Specifically, we exclude all signals classified as discrete in the Open Source Asset Pricing database. In addition, we drop the following signals due to poor coverage (fewer than 200 firms in any given month) or because they exhibit discrete-like beahvior: *Activism1*, *Activism2*, *AgeIPO*, *EarnSupBig*, *FirmAgeMomm*, *IO_ShortInterest*, *IndRetBig*, *NumEarnIncrease*, *PS*, *ProbInformedTrading*, *RDAbility*, and *RDcap*.

returns (RET) are the most volatile, with an annualized mean of 1.07% and a standard deviation of 12.55%. In contrast, ICC factor returns (Panel C) are on average lower (0.25%) and substantially less volatile (1.77%), consistent with their forward-looking nature and smaller cross-sectional variation. On average, carbon tilts under both RET and ICC are moderately positive for unscaled emissions and near zero or slightly negative for scaled emissions, suggesting that many strategies tilt toward large emitters that may be relatively efficient on a per-unit-of-output basis. The median tilt in carbon intensity is positive, but there is considerable variation across strategies and over time. Some factors consistently overweight green firms, while others exhibit strong brown tilts.

Panels D and E present summary statistics for MW and GLB returns within the S&P500 universe. Average returns are negative (-0.24% and -0.12%, respectively), but with significant dispersion in the interquartile range. Carbon tilt patterns mirror those in the full sample: average tilts are positive for unscaled emissions and negative for scaled emissions. Importantly, there is still substantial cross-sectional variation in these measures across strategies.

[Insert Figure 3 about here]

Figure 3 plots average annualized factor returns and carbon tilts by factor category for each expected return proxy. Most factor groups earn positive realized returns (RET), ranging from 0.17% to 2.72%, except the frictions category, which exhibits slightly negative performance. In contrast, ICC returns are negative for profitability, momentum, and friction-related factors, but positive for valuation and intangibles (0.76% and 1.46%, respectively). More importantly, carbon tilts vary systematically across factor groups. Valuation, intangibles, and earnings-based factors tilt toward high-emitting firms, whereas profitability-based factors favor low-emitting firms. On the other hand, friction and momentum-based factors tilt towards carbon-intensive firms, whereas valuation, profitability, and risk-based factors favor carbon-efficient firms. MW and GLB returns are positive for valuation, risk, and intangibles factors, but show substantial differences in their returns, suggesting that higher-order moments can impact expectation formation.

Carbon tilts in the S&P 500 sample broadly follow the same patterns as in the full sample, corroborating the consistency of carbon exposures across factor groups and return proxies.

2.4. Climate concerns and shocks

We use the Media Climate Change Concerns (MCCC) index from Ardia et al. (2023) to capture shifts in climate concerns.[9] Following Pástor et al. (2022) and Ardia et al. (2023), we measure shocks to climate concerns as prediction errors derived from an explanatory-variables-augmented autoregressive (ARX(1)) model applied to the MCCC index. Specifically, using a rolling window of 60 observations, we regress the MCCC index on its lagged values and a set of explanatory variables chosen to capture financial, energy, and macroeconomic developments. Specifically, we consider the excess market return, the default spread, the term spread, VIX, EPU, and oil, gas, and propane returns. The prediction error for month t is then defined as the realized MCCC value minus its predicted value from the ARX(1) model, which we use as a proxy for unanticipated changes in climate concerns.

2.5. Climate exposures

As a "soft" complement to the "hard" measures based on carbon emissions, we consider firm-level climate change exposures from Sautner et al. (2023a).[10] Specifically, we consider their aggregate exposure measure, *CCExposure*, which captures the attention paid to climate-related words in general, together with measures specifically related to opportunity, regulatory, and physical climate risks. These measures are constructed from earnings conference call transcripts and capture the share of the discussion devoted to climate-related topics, following the methodology of Hassan, Hollander, van Lent, and Tahoun (2019) and Hassan, Hollander, van Lent, Schwedeler, and Tahoun (2023). Earnings calls serve as an important channel for firms, analysts, and stakeholders to communicate and interpret information. The fraction of firms that discuss climate change has increased steadily during our sample period.

[9] Updated data are available at https://sentometrics-research.com/download/mccc/.

[10] The data are provided by the authors: doi.org/10.17605/OSF.IO/FD6JQ.

2.6. Control variables

To complete our dataset for the analysis, we collect a broad set of control variables capturing common risk factors, macroeconomic conditions, and energy market developments. We obtain excess market returns, Fama and French (1993, 2015) factors (SMB, HML, RMW, and CMA), and the Carhart (1997) MOM factor from Kenneth French's website. Additionally, we collect the Pástor and Stambaugh (2003) liquidity factor from Lubos Pástor's website. To account for financial market conditions, we collect data on the VIX index, the term spread (10-year Treasury yields less the 3-month T-bill rate), and the default spread (BAA minus AAA-rated corporate bonds yields). We also include the U.S. economic policy uncertainty (EPU) index of Baker, Bloom, and Davis (2016). To capture energy market dynamics relevant for transition risk, we include returns on West Texas Intermediate (WTI) crude oil, Henry Hub natural gas, and Mont Belvieu Texas propane from the Federal Reserve Bank of St. Louis (FRED). Finally, we include monthly log changes in the consumer price index, industrial production, and non-farm payroll employment, also from FRED, to control for economic activity.

3. Carbon tilts and factor returns

This section explores whether and how carbon tilts influence expected factor returns. We first estimate the carbon tilt premium in the cross-section of factor returns using both RET and ICC returns. We then examine dynamic effects in the carbon tilt premium by interacting it with unexpected shifts in climate concerns and, secondly, with a linear time trend to assess its time-series evolution during our sample period.

3.1. Are carbon transition risks reflected in factor returns?

We begin our analysis by investigating the cross-sectional relationship between factor-level carbon tilts and expected returns. Specifically, we estimate the regression model

$$\widehat{E}_t^p\left[f_{i,t+1}\right] = \alpha + \beta \text{Carbon tilt}_{i,t} + \gamma' \text{Controls}_{i,t} + \delta_t + \lambda_g + \varepsilon_{i,t}, \tag{1}$$

where $\widehat{E}_t^p[f_{i,t+1}]$ denotes the expected return on factor $i = 1, \ldots, 160$ at time t based on expected return proxy $p \in \{\text{RET}, \text{ICC}\}$. The main variable, $\text{Carbon tilt}_{i,t}$, captures the factor's value-weighted carbon tilt measured using Scope 1 and Scope 1+2 total emissions and emission intensity, respectively. $\text{Controls}_{i,t}$ is a vector of control variables known to capture cross-sectional variation in returns (discussed in Section 2.6). We also include year (δ_t) and factor group (λ_g) fixed effects to account for common shocks and time-invariant differences across investment styles, respectively. The regression is run at the factor-month level, and standard errors are clustered by factor. Our coefficient of interest is β. To ease interpretation, we standardize carbon tilts to have zero mean and unit variance throughout our regressions, so the coefficient can be interpreted as the annualized carbon tilt premium in percentage points per standard deviation increase in carbon tilts. Our regressions always include the same number of observations: 160 factors and 156 months, for a total of 24,960 factor-month observations.

3.1.1. Realized returns Panel A of Table 2 shows that carbon tilts are negatively associated with realized returns (RET) across all emissions measures. The carbon tilt premia are consistently negative and statistically significant, ranging from -1.52 (t-statistic of -6.39) to -1.59 (t-statistic of -6.40) for total emissions and from -0.99 (t-statistic of -4.50) to -1.06 (t-statistic of -3.63) for emission intensity. These effects are economically meaningful: a one-standard-deviation increase in carbon tilts is associated with a decline in annualized monthly returns of about 1.5% for total emissions and 1.0% for emission intensity. Because Table 1 shows substantial heterogeneity in carbon tilts across factor groups, we estimate the regressions both with and without group fixed effects to assess if our results are driven by group effects. Including factor group fixed effects (Column (2)) slightly improves model fit and the magnitude of the coefficient, but the overall effects are small, suggesting that the RET results are not driven by differences in investment style.

[Insert Table 2 about here]

These findings indicate that factors tilted toward high-emitting and low-efficiency firms tend to underperform on a realized return basis, suggesting a negative carbon premium when RET is used as a proxy for expected returns. These findings align with Zhang (2025), who also finds a negative carbon premium in realized returns using point-in-time emission intensity data. We interpret the negative carbon premium in RET as evidence of an ongoing transition to a low-carbon equilibrium, during which investors reallocate capital away from carbon-intensive firms toward greener alternatives. Such decarbonization efforts would be consistent with the observed underperformance. However, since RET may be a poor proxy for expected returns in short sample periods (Eskildsen et al., 2024), we next turn to forward-looking return measures based on the implied cost of capital (ICC).

3.1.2. Implied cost of capital Panel B of Table 2 presents results for ICC-based expected returns. In contrast to the RET results, we find a positive relationship between carbon tilts and factor returns. Coefficients range from 0.02 (t-statistic of 0.35) to 0.13 (t-statistic of 2.33) for total emissions and from 0.21 (t-statistic of 2.58) to 0.41 (t-statistic of 6.05) for emission intensity. Notably, emission intensity emerges as the strongest predictor of ICC factor returns: not only are coefficients larger in magnitude, but they are also statistically more significant and account for a greater share of cross-sectional variation. While factor group effects had a limited impact on RET results, adding factor group fixed effects in Column (2) increases explanatory power across all carbon risk measures. Moreover, the inclusion attenuates both the magnitude and significance of the coefficients for total emissions, whereas the coefficients for emission intensity maintain their magnitude and significance. The coefficients for emission intensity suggest an annualized carbon tilt premium between 0.21% and 0.41% for ICC returns, which is about the same magnitude documented in Eskildsen et al. (2024) for individual returns.

Taken together, our results reveal a nuanced relationship between carbon tilts and expected factor returns. RET points to an underperformance of carbon-intensive strategies, consistent with divestment and reallocation trends during the transition to a low-carbon equilibrium. In contrast, ICC returns indicate a positive carbon premium, suggesting that investors demand compensation for bearing carbon risk. Our results are consistent with a discount-rate channel in which investors' green preferences make them divest and reprice brown assets, increasing their cost of capital as captured by ICC returns.

3.2. Unanticipated climate concerns

Our baseline analysis shows that factors tilted toward carbon-intensive firms earn lower returns when using RET as a proxy for expected returns. One plausible explanation for this finding is that concerns about climate change have strengthened unexpectedly over our sample period. Pástor et al. (2022) show that shocks to climate concerns drive the positive performance of their Green-Minus-Brown (GMB) factor, which vanishes once the shocks are accounted for. To examine whether climate shocks influence the carbon tilt premium in factor returns, we interact carbon tilts with unexpected climate shocks in the regression

$$\begin{aligned}\widehat{E}_t^p\left[f_{i,t+1}\right] =& \alpha + \beta_1 \text{Carbon tilt}_{i,t} + \beta_2 \Delta\text{Concern}_t + \beta_3\left(\text{Carbon tilt}_{i,t} \times \Delta\text{Concern}_t\right) \\ &+ \gamma' \text{Controls}_{i,t} + \delta_t + \lambda_g + \varepsilon_{i,t},\end{aligned} \tag{2}$$

where $\Delta\text{Concern}_t$ captures unanticipated climate shocks, computed as prediction errors from the Ardia et al. (2023) Media Climate Change Concerns index (MCCC). The coefficient of interest is β_3, which measures whether the carbon tilt premium varies with unexpected shifts in climate concerns. As above, we standardize carbon tilts to ease interpretations.

[Insert Table 3 about here]

Panel A of Table 3 shows that unanticipated climate shocks reduce, and even reverse, the negative carbon tilt premium for RET. The interaction term is positive and significant across all specifications, ranging from 2.52 (t-statistic of 2.95) to 3.06 (t-statistic of 4.10) for total emissions and from 3.21 (t-statistic of 4.47) to 3.36 (t-statistic of 4.60) for emission intensity. Including factor group fixed effects leaves both the economic and statistical significance of the results largely unchanged. $\Delta\text{Concern}_t$ ranges from a high of 1.34 to a low of -0.86, with a mean of 0.089. These findings suggest that the negative carbon premium in realized returns is at least partly attributable to unexpected increases in climate concern during our sample period.

Panel B documents that ICC returns similarly increase for carbon-intensive factors when climate concerns rise. The interaction terms are again positive and significant, ranging from 0.14 to 0.17 (t-statistics from 2.81 to 3.37) for total emissions and from 0.27 to 0.28 (t-statistics above 6 in both cases) for emission intensity. Although the main effect of carbon tilts becomes statistically insignificant once group fixed effects are included, the magnitude of the interaction effect remains similar, and explanatory power increases markedly. This implies that investors raise the discount rates of carbon-intensive firms more sharply in periods of heightened climate concern. Altogether, the evidence so far points to a carbon premium in factor returns that varies with unanticipated shifts in climate concern. Next, we further explore its time-series evolution.

3.3. Carbon tilt premia over time

This section examines the evolution of carbon tilt premia over time. Specifically, we assess whether the pricing of carbon risk has changed by estimating the baseline regression from (1) using 36-month rolling windows from January 2015 to December 2022.

[Insert Figure 4 about here]

Figure 4 plots the estimated rolling-window carbon tilt coefficients for RET and ICC returns for each of the four emission measures. Solid lines denote statistically significant coefficients, while dotted lines indicate insignificance. The RET carbon tilt premium is declining over time for most of the sample, though it rises sharply near the end of the sample. The negative carbon premium is significant for most periods using total emissions and for emission intensity from 2018 onward. Turning to forward-looking returns, we find that the ICC carbon premium increases over the period. ICC carbon premia based on emission intensity are consistently positive, whereas ICC carbon premia for total emissions are negative during the first part of the sample but become positive around 2018. These results are consistent with a repricing of carbon risk as investors gradually incorporate climate-related risks more systematically into asset prices as part of transitioning to a "carbon-aware" economy. In recent years, forward-looking carbon premia have turned consistently positive, suggesting that sustainable investing practices may be affecting the cost of capital for carbon-intensive firms.

To formally test whether carbon tilt premia significantly changed over time, we estimate the following regression model

$$\widehat{E}_t^p\left[f_{i,t+1}\right] = \alpha + (\beta_1 + \beta_2 \text{Time})\,\text{Carbon tilt}_{i,t} + \gamma' \text{Controls}_{i,t} + \delta_t + \lambda_g + \varepsilon_{i,t}, \quad (3)$$

where $\text{Time} = \frac{t - t_{\text{start}}}{t_{\text{end}} - t_{\text{start}}}$ is a time trend that increases linearly from zero to one over the sample. The remaining variables are described in (1). In this regression, β_1 is the carbon premium at the beginning of the sample period, and $\beta_1 + \beta_2$ is the carbon premium at the end of the sample period. Thus, β_2 measures the change in the carbon tilt premium.

[Insert Figure 5 about here]

Figure 5 displays the baseline estimates β_1 and the trend interaction coefficients β_2 for RET and ICC returns across all four carbon measures. Consistent with the rolling window results, RET premia are initially negative, two significantly so (intensity), and all have modestly negative time trends. In contrast, ICC-based premia exhibit strongly positive and significant time trends for all measures. For example, the Scope 1 emission intensity carbon tilt premium rises from an initial estimate of $\beta_1 = -0.21$ to $\beta_1 + \beta_2 = 0.88$ at the end of the sample.

Altogether, our results are consistent with a gradual repricing of carbon risk and decarbonization of portfolios that have led heavy-emitters and carbon-inefficient firms to underperform in realized returns. At the same time, our findings document a strong and positive carbon tilt premium in forward-looking ICC returns that has increased over time. In this setting, emission intensity emerges as the most reliable and economically meaningful measure, likely due to its cross-sectional comparability, which becomes useful in a factor portfolio setting.

4. Carbon tilts across investment styles

This section explores heterogeneity in carbon tilt premia across investment styles. We begin by estimating our baseline specification for each group separately to gauge differences in the pricing of carbon risk across categories. We then extend the analysis to include dynamic effects by (i) interacting carbon tilts with unexpected shifts in climate concerns and (ii) tracking the evolution of carbon premia over time within each group to assess whether the incorporation of climate risk differs by investment style.

4.1. Are carbon transition risks reflected across groups?

Figure 6 displays regression coefficients for each factor group, with error bars denoting standard errors clustered at the factor level. While we observe some heterogeneity across factor groups in the magnitude of the carbon tilt premia, they are most negative. These effects are most pronounced for earnings, momentum, and profitability factors for total emissions, and intangibles and profitability factors for emission intensity.

[Insert Figure 6 about here]

In contrast, ICC-based carbon tilt premia are most positive, especially for emission intensity. We find a significant negative carbon tilt premium for frictions in total emissions, but positive and significant premia for momentum and profitability factors. The carbon premia are more pronounced for emission intensity. Here, we find positive and significant coefficients for intangibles, investment, profitability, and valuation factors. These are categories whose long legs are often associated with "brown" firms. This supports the idea that investors demand a risk premium for carbon-intensive exposures, particularly in factor groups linked to firm fundamentals such as operational efficiency, expansionary behavior, and long-term value creation.

4.2. What about responses to unanticipated climate concerns?

Figure 7 plots the interaction coefficients between carbon tilts and climate shocks for each factor group. Consistent with our baseline findings, interaction terms are consistently positive across factor groups in realized returns, and several are significant, e.g., valuation under emission intensity. This indicates that climate shocks reduce the negative carbon tilt premium of carbon-tilted factors and, when accounting for the effects of climate shocks, can turn the estimated carbon premium positive.

[Insert Figure 7 about here]

While we again observe some heterogeneity, we find mostly positive interactions for ICC returns. The dynamic effects are strongest for emission intensity, where almost all interactions are significantly positive, except for frictions and intangibles. Although magnitudes are comparable, we do find that the estimated carbon tilt premium is both larger and more precisely estimated for investment, profitability, and valuation factors.

4.3. Carbon premia across time and groups

This section investigates the time-series evolution of carbon tilt premia across factor groups. To capture these dynamics, we estimate the baseline regression from (1) separately for each factor group using a 36-month rolling window from January 2015 to December 2022. Statistically significant coefficient estimates are indicated by solid lines, whereas dotted lines indicate insignificance.

[Insert Figures 8 and 9 about here]

Figure 8 presents rolling-window estimates of carbon tilt premia based on RET across groups and emission measures. While the overall pattern mirrors the negative and declining carbon premium documented in Figure 4, substantial variation emerges across groups. For example, earnings factors exhibit a positive carbon premium for scaled emissions in the early sample period, while momentum and frictions appear largely neutral between 2016 and 2020, particularly for emission intensity.

Figure 9 plots rolling-window estimates of ICC carbon tilt premia. ICC carbon premia tell a straightforward story: carbon tilt premia have increased over time for all factor groups. While initially low, and in some cases negative, carbon tilt premia have steadily increased over the sample period. Formal tests using the regression in (3) for each factor group confirm statistically significant increases in carbon premia over time for investment, momentum, profitability, and valuation factors. The results, which are reported in the Internet Appendix, suggest that the pricing of carbon risk is more pronounced in investment styles tied to value-based and past performance.

In sum, while some heterogeneity exists across factor groups, four main patterns emerge: (i) carbon tilt premia are mostly negative in realized returns and largest for total emissions, (ii) ICC-based carbon tilt premia are generally positive and significant, especially for investment, profitability, and valuation factors, (iii) both RET and ICC carbon premia increase with climate shocks, and (iv) ICC carbon tilt premia have increased significantly over time for investment, momentum, profitability, and valuation factors.

5. Option-implied expected returns

This section examines an alternative set of forward-looking expected returns derived from option prices. Specifically, we consider the lower bounds on the stock-level expected return from Martin and Wagner (2019) and Chabi-Yo et al. (2023b). We analyze these measures separately as they are only available for S&P500 firms. Following our baseline procedure, we construct 160 long-short factors using S&P500 constituents and estimate the baseline, dynamic, and time-trend regressions to assess the carbon tilt premium for option-implied expected returns. While this allows us to assess the robustness of our findings, we emphasize that the results are not directly comparable due to differences in the investment universe. Moreover, while ICC provides a direct estimate of expected returns, MW and GLB only provide lower bounds on expected returns.

5.1. Option-implied carbon tilt premia

Table 4 reports results for our baseline regression in (1) (Column (1)) and the dynamic regression in (2) (Column (2)). We include factor group and year fixed effects in both regressions, and cluster standard errors by factor.

[Insert Table 4 about here]

Panel A of Table 4 presents results for MW factor returns. The coefficients tell a tale of two emission measures. While carbon tilts are negatively related to MW returns for total emissions (coefficients between -0.31 and -0.37, t-statistics from -4.67 to -5.14), the relationship reverses for intensity-based measures (coefficients between 0.26 and 0.41, t-statistics from 3.20 to 4.83). That is, we estimate a negative carbon tilt premium for total emission, but a positive carbon tilt premium for emission intensity using MW factor returns. These results highlight a sharp distinction between absolute and relative emissions in how carbon risk is priced by the options market.

Panel B of Table 4 considers GLB factor returns. The carbon tilt premium is negative for total emissions (coefficients between -0.27 to -0.31, t-statistics from -4.42 to -4.82) and positive for emission intensity (0.06 to 0.15, t-statistics from 0.79 to 1.84). The GLB carbon tilt premium is noticeably smaller and less significant compared to MW returns, suggesting that carbon pricing may be influenced by differences in higher-order risk-neutral moments (see also Eskildsen et al. (2024) for a similar conclusion).

The dynamic effects also differ across option-implied expected returns. For MW returns, carbon premia increase in response to unanticipated increases in climate concerns for total emissions (coefficients of 0.21 and 0.22 with t-statistics of 3.19 and 3.36), but decrease for emission intensity (coefficients of -0.16 to -0.22, t-statistics of -2.54 and -4.27). In contrast, GLB returns exhibit consistently negative interaction effects: the carbon tilt premium declines with climate shocks for both total emissions (-0.35 to -0.41, t-statistics from -4.21 to -5.34) and emission intensity (-0.75 to -0.88, t-statistics from -6.47 to -8.19). These results point to important differences in both carbon transition risk measures and alternative forward-looking return proxies.[11]

5.2. Time-trend regressions for option-implied returns

Figure 10 presents baseline coefficient estimates β_1 and trend interaction coefficients β_2 from (3) for MW and GLB returns across all four carbon measures.

[11]A potential concern with option-implied measures has recently been raised by Schriendorfer and Sichert (2025). They show that the bound in Martin (2017), which features in Martin and Wagner (2019), is not always tight. Specifically, they find a non-tight bound during times of low volatility and a violated bound during market stress.

[Insert Figure 10 about here]

MW returns are positive for total emissions and negative for emission intensity, but the interaction coefficients are all positive and highly significant. This points to a significant increase in the MW carbon tilt premium over time for all emission measures. In contrast, the evolution of carbon tilt premia in GLB returns depends on the specific risk measure. The initial coefficients are positive for total emissions and negative for emission intensity. The interaction coefficients are negative and significant for total emissions, but insignificant for emission intensity, although the point estimate is slightly positive. In the Internet Appendix, we show that some of these contrasting results may be related to the COVID-19 crisis, during which the option-implied returns spike strongly.

6. Additional results and robustness

This section presents additional results and robustness checks. First, we re-estimate our baseline regressions using only firms with reported emissions, excluding estimated emission numbers to verify that our findings are not driven by vendor-driven imputations. Second, we implement an alternative estimation approach using Fama and MacBeth (1973) regressions. Third, we construct a composite green score that aggregates our carbon transition risk measures into a single proxy, following Eskildsen et al. (2024). Last, we show that our main conclusions are robust to using an alternative measure of firm-level climate change exposures from Sautner et al. (2023a), who provide a text-based proxy of climate risks from earnings call transcripts.

6.1. Reported emissions

The use of estimated emissions has recently been debated in the literature (Bolton and Kacperczyk, 2021, 2023, Aswani et al., 2024), because vendor-supplied estimates are subject to revisions and vary across methodologies. Conversely, Busch, Johnson, and Pioch (2022) find that firm-reported Scope 1 and 2 emissions are consistent across data providers, suggesting that reported emissions may be more reliable. To address these concerns, we re-estimate the baseline and dynamic regressions using the subsample of firms that disclose emissions.

[Insert Table 5 about here]

Table 5 reports results for RET and ICC returns with year and group fixed effects. The main takeaway is straightforward: the results closely mirror our baseline findings for reported and estimated emissions. Across both return proxies, we find comparable coefficients in sign, magnitude, and statistical significance. If anything, the effects are slightly stronger for reported emissions. RET exhibits a significantly negative carbon premium across emission measures, while ICC returns show a positive and significant premium for emission intensity (but not total emissions). Interacting carbon tilts with unanticipated climate concerns yield positive and significant coefficient estimates for all return proxies and emission measures, consistent with our baseline interpretations.

Altogether, these findings confirm that our main findings are not driven by vendor-estimated emission numbers. Since more than 95% of firms in our LSEG sample disclose emissions, this is not surprising, but still reassuring that vendor-supplied estimates are not affecting our main conclusions.

6.2. Fama-MacBeth regressions

Our benchmark results are based on pooled cross-sectional regressions. This section estimates carbon tilt premia for each of the four proxies for carbon transition risk using Fama and MacBeth (1973) regressions. Specifically, for each month, we estimate the following cross-sectional regression

$$\widehat{E}_t^p\left[f_{i,t+1}\right] = \lambda_{0,t} + \lambda_{1,t}\text{Carbon tilt}_{i,t} + \lambda_{2,t}'\beta_{i,t} + \varepsilon_{i,t}, \tag{4}$$

where $\beta_{i,t}$ is a vector of factor loadings for the Fama and French (1993, 2015) factors and momentum (Carhart, 1997) estimated using full-sample time series regressions for each factor portfolio. We are interested in the time-series average $\lambda_{1,t}$, which estimates the carbon tilt premium.

[Insert Figure 11 about here]

Figure 11 plots the time-series averages of $\lambda_{1,t}$ with error bars based on Fama and MacBeth (1973) standard errors across RET and ICC returns for the four carbon risk measures. Consistent with our main findings, RET-based premia are negative across all carbon measures, although not statistically significant at conventional levels. Similarly, we find that carbon tilts are strong positive predictors of expected factor returns in the cross-section of ICC factor returns. Altogether, these results confirm our benchmark evidence from pooled regressions and provide further support for a significantly positive carbon tilt premium in forward-looking expected returns.

6.3. A composite carbon score

Our main analysis treats total emissions and emission intensity as separate proxies for carbon transition risk. However, as recently emphasized by Eskildsen et al. (2024), investors may disagree about how to measure carbon risk, and "greenness" in general. Motivated by their work, we construct a composite carbon score as a weighted average across our four carbon risk measures: Scope 1 and Scope 1+2 scaled and unscaled emissions. Specifically, we first standardize each emission measure to have zero mean and unit variance within each month. We then average across the four standardized measures for each stock and standardize the composite measure within each month.

[Insert Figure 12 about here]

Figure 12 summarizes our main results for the composite carbon score. The top panel reports estimated coefficients from the baseline regression in (1). Consistent with our benchmark analysis, we find a significantly negative carbon premium for RET and a significantly positive premium for ICC. The middle panel displays results from the dynamic regression in (2). As previously, unanticipated climate shocks offset the negative carbon premium in realized returns and amplify the positive premium in ICC. Last, the bottom panel illustrates the time-series evolution using the time trend regression in (3). We find that the carbon score-based carbon premium is initially negative for RET and

ICC but increases significantly over time. Overall, the results confirm our baseline findings and lie somewhere between the results for total emissions and emission intensity.

6.4. Climate exposures and factor returns

Table 6 examines how climate tilts, defined as value-weighted differences in firm-level climate change exposures from Sautner et al. (2023a), influence expected factor returns. We follow Sautner et al. (2023b) and exponentially smooth monthly forward-filled observations of the exposure measures using a half-life of three months. This approach acknowledges that when a specific climate topic has been discussed in an earnings call, subsequent calls may not pick up the same topic again. Not because the risk has vanished, but because it was covered in a recent call. Using climate tilts allows us to test if our benchmark findings extend to other measures of climate risks.

[Insert Table 6 about here]

Panel A of Table 6 demonstrates that we obtain a negative climate tilt premium for general climate change exposure (-0.96, t-statistic of -3.76) and transition opportunities (-1.02, t-statistic of -3.57). In contrast, there is little evidence for a premium associated with regulatory climate risks. Interestingly, we find a positive and significant climate tilt premium in RET for physical climate risks (coefficient of 0.72, t-statistic of 3.28), suggesting that investors reward exposures to firms better positioned to manage physical climate threats. That transition and physical risk can be priced differently is also noted in Giglio et al. (2021). Interacting climate tilts with unanticipated climate concerns, we find positive and significant coefficients for general climate change exposure (3.68, t-statistic of 3.62), transition opportunities (4.20, t-statistic of 4.29), and physical climate risks (3.43, t-statistic of 4.78). Overall, these results mirror those for carbon transition risk and confirm that factor returns are influenced by climate considerations.

Panel B presents results for ICC returns. We find positive and significant premia for climate change (0.20, t-statistic of 3.01), opportunity (0.17, t-statistic of 2.49), and regulatory tilts (0.29, t-statistic of 4.82). Physical risk tilts, however, show no significant relation to ICC factor returns. Adding an interaction term for unanticipated climate concerns strengthens these effects. The coefficients for climate change (0.21, t-statistic of 5.40), opportunity (0.12, t-statistic of 4.13), regulatory (0.33, t-statistic of 6.54), and physical tilts (0.24, t-statistic of 4.91) are all significant and positive.

Overall, these findings corroborate our benchmark analyses based on carbon tilts. We find negative carbon and climate tilt premia in realized returns, whereas we find strong and persistent evidence of a positive and significant carbon and climate premium in forward-looking ICC returns that increase with time.

7. Concluding remarks

Curbing carbon emissions is essential for limiting global warming and staying within the limits of the Paris Agreement. A central question in asset pricing is how the transition to a low-carbon economy will impact asset prices and investment strategies. We address this by studying the link between carbon risk and expected factor portfolio returns. Specifically, we construct 160 U.S. equity factor portfolios and quantify their time-varying carbon exposure using carbon tilts, defined as the value-weighted difference in carbon risk (total emissions or emission intensity) between a factor's long and short legs.

Using realized returns, we find a negative carbon tilt premium. In contrast, we find a positive and significant carbon tilt premium using forward-looking expected returns based on the implied cost of capital. This premium increases with unanticipated climate concerns and over time. Our results are consistent with high-carbon divestments amid increased climate awareness and a gradual repricing of carbon risk. Carbon tilt premia also exhibit heterogeneity across investment styles. Profitability, investment, and valuation factors exhibit the largest and most precisely estimated carbon tilt premium and the largest increase in premia over time. These results suggest that carbon transition risk is not uniformly priced across factors, but is instead concentrated in strategies linked to firm fundamentals such as operational efficiency, expansionary behavior, and long-term value.

Our empirical findings carry important implications for asset pricing, asset allocation practices, and climate finance. The increasing pricing of carbon risk in expected returns suggests that investors are responding to climate-related risks. Investors and regulators should recognize that carbon exposure meaningfully affects the performance of investment strategies widely used in the industry and that climate risk is not uniformly priced across styles. These insights support initiatives aimed at enhancing transparency around firms' carbon footprints and highlight the need for consistent climate-related disclosures to ensure accurate assessments of carbon risks.

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Table 1: Descriptive statistics

This table reports summary statistics for firm-level variables (Panel A) and factor-level long–short portfolios (Panels B–E). Panel A reports means, standard deviations, medians, and interquartile ranges for firm-level stock returns and carbon emissions. Panels B–E show the corresponding statistics for factor returns and carbon tilts. RET denotes realized excess returns, ICC is the implied cost of capital, and MW and GLB are option-implied lower bounds on expected returns. MW and GLB are available only for S&P 500 constituents. All returns are annualized. Scope 1 and Scope 1+2 emissions are measured in megatonnes of CO_2 equivalents (MtCO2e). Emission intensity is defined as MtCO2e divided by sales, scaled by 100 for readability. The sample period is 2010 to 2022.

			Percentiles		
Variables	Mean	Std	25	50	75
Panel A: Firm-level data					
RET	14.99	39.96	-53.86	12.70	76.94
ICC	8.66	3.59	6.47	8.17	10.20
MW	4.96	6.74	1.61	3.23	5.98
GLB	8.57	9.77	3.64	5.98	10.21
S1 MtCO2e	4.14	13.89	0.01	0.09	0.98
S1+2 MtCO2e	4.48	13.61	0.08	0.34	1.94
S1 MtCO2e/sales/100	3.75	10.53	0.03	0.14	1.86
S1+2 MtCO2e/sales/100	3.87	9.66	0.15	0.46	2.68
Panel B: Factor-level data (RET)					
RET	1.07	12.55	-22.65	0.49	24.35
S1 MtCO2e	0.89	15.26	-4.24	0.15	5.73
S1+2 MtCO2e	1.17	16.18	-4.26	0.22	5.93
S1 MtCO2e/sales/100	-0.19	4.08	-1.61	0.04	1.58
S1+2 MtCO2e/sales/100	-0.09	3.14	-1.42	0.02	1.45
Panel C: Factor-level data (ICC)					
ICC	0.25	1.77	-0.87	0.17	1.21
S1 MtCO2e	0.99	15.48	-4.30	0.18	5.95
S1+2 MtCO2e	1.26	16.46	-4.36	0.26	6.21
S1 MtCO2e/sales/100	-0.18	4.13	-1.57	0.04	1.52
S1+2 MtCO2e/sales/100	-0.08	3.14	-1.37	0.02	1.42
Panel D: Factor-level data (MW)					
MW	-0.24	3.10	-1.05	-0.11	0.74
S1 MtCO2e	0.93	15.99	-4.64	0.12	6.50
S1+2 MtCO2e	1.24	16.92	-4.80	0.20	6.65
S1 MtCO2e/sales/100	-0.15	4.51	-1.57	0.04	1.60
S1+2 MtCO2e/sales/100	-0.04	3.28	-1.29	0.04	1.41
Panel E: Factor-level data (GLB)					
GLB	-0.12	3.62	-0.89	-0.05	0.75
S1 MtCO2e	0.93	15.99	-4.64	0.12	6.50
S1+2 MtCO2e	1.24	16.92	-4.80	0.20	6.65
S1 MtCO2e/sales/100	-0.15	4.51	-1.57	0.04	1.60
S1+2 MtCO2e/sales/100	-0.04	3.28	-1.29	0.04	1.41

Table 2: Carbon tilts and factor returns

This table reports carbon tilt coefficients from the regression model in (1) with t-statistics based on standard errors clustered at the factor level (in parentheses). All regressions include control variables (described in Section 2.6). Column (1) includes year fixed effects, and Column (2) includes year and factor group fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Panel A reports results for realized returns (RET) and Panel B reports results for forward-looking implied cost of capital (ICC) returns. Each regression is based on 24,960 factor-month observations (160 factors and 156 months). The sample period is 2010 to 2022.

	S1 Emissions		S1+2 Emissions		S1 Intensity		S1+2 Intensity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Realized returns (RET)								
Carbon tilt	-1.52	-1.59	-1.52	-1.59	-0.99	-1.02	-1.03	-1.06
	(-6.53)	(-6.40)	(-6.39)	(-6.28)	(-4.50)	(-4.23)	(-3.85)	(-3.63)
R^2 (%)	2.27	2.31	2.34	2.39	2.08	2.12	2.17	2.20
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: Implied cost of capital (ICC)								
Carbon tilt	0.13	0.03	0.13	0.02	0.21	0.22	0.41	0.41
	(2.33)	(0.58)	(2.19)	(0.35)	(2.58)	(3.67)	(4.48)	(6.05)
R^2 (%)	2.65	11.90	2.61	11.55	3.72	15.38	8.14	19.24
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 3: Unanticipated climate shocks

This table reports carbon tilt coefficients and interaction terms for unanticipated climate concerns from the regression model in (2) with t-statistics based on standard errors clustered at the factor level (in parentheses). All regressions include control variables (described in Section 2.6). Column (1) includes year fixed effects, and Column (2) includes year and factor group fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. ΔConcern is computed as prediction errors from an ARX(1)-model for the MCCC index of Ardia et al. (2023). Panel A reports results for realized returns (RET) and Panel B reports results for forward-looking implied cost of capital (ICC) returns. Each regression is based on 24,960 factor-month observations (160 factors and 156 months). The sample period is 2010 to 2022.

	S1 Emissions		S1+2 Emissions		S1 Intensity		S1+2 Intensity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Realized returns (RET)								
Carbon tilt	-1.70	-1.76	-1.67	-1.74	-1.21	-1.24	-1.29	-1.32
	(-7.01)	(-6.92)	(-6.74)	(-6.67)	(-5.28)	(-5.00)	(-4.78)	(-4.52)
Δ Concern	-0.18	-0.18	-0.08	-0.08	-0.01	-0.01	-0.02	-0.02
	(-0.26)	(-0.25)	(-0.10)	(-0.10)	(-0.01)	(-0.01)	(-0.02)	(-0.02)
Interaction	3.06	3.05	2.53	2.52	3.36	3.35	3.22	3.21
	(4.10)	(4.04)	(3.00)	(2.95)	(4.60)	(4.57)	(4.50)	(4.47)
R^2 (%)	2.30	2.35	2.37	2.41	2.13	2.17	2.22	2.25
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: Implied cost of capital (ICC)								
Carbon tilt	0.12	0.02	0.12	0.01	0.19	0.21	0.38	0.39
	(2.23)	(0.46)	(2.09)	(0.22)	(2.41)	(3.46)	(4.31)	(5.88)
Δ Concern	-0.03	-0.03	-0.03	-0.03	0.00	0.00	0.00	0.00
	(-1.36)	(-1.37)	(-1.62)	(-1.65)	(0.02)	(0.01)	(0.01)	(0.01)
Interaction	0.15	0.14	0.17	0.14	0.28	0.28	0.27	0.27
	(3.16)	(2.81)	(3.37)	(2.96)	(6.18)	(6.28)	(6.95)	(6.95)
R^2 (%)	2.72	11.95	2.69	11.61	3.95	15.61	8.40	19.49
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 4: option-implied expected returns

This table reports carbon tilt coefficients and interaction terms for unanticipated climate concerns based on option-implied expected returns with *t*-statistics based on standard errors clustered at the factor level (in parentheses). All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Column (1) contains baseline regressions from (1). Column (2) reports interaction terms from the dynamic model in (2). Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Unanticipated climate concerns are computed as prediction errors from an ARX(1)-model for the MCCC index of Ardia et al. (2023). Panel A reports results for Martin and Wagner (2019) (MW) returns and Panel B for Chabi-Yo et al. (2023b) (GLB) returns. The underlying factors are constructed from S&P500 constituents. Each regression is based on 24,960 factor-month observations (160 factors and 156 months). The sample period is 2010 to 2022.

	S1 Emissions		S1+2 Emissions		S1 Intensity		S1+2 Intensity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Martin-Wagner bounds								
Carbon tilt	-0.31	-0.32	-0.37	-0.38	0.26	0.27	0.41	0.43
	(-4.67)	(-4.74)	(-5.14)	(-5.18)	(3.20)	(3.28)	(4.83)	(4.99)
Interaction		0.22		0.21		-0.16		-0.22
		(3.36)		(3.19)		(-2.54)		(-4.27)
R^2 (%)	3.13	3.18	3.44	3.48	2.90	2.92	3.85	3.90
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Chabi-Yo, Dim, and Vilkov bounds								
Carbon tilt	-0.27	-0.25	-0.31	-0.30	0.06	0.11	0.15	0.22
	(-4.42)	(-3.98)	(-4.82)	(-4.44)	(0.79)	(1.35)	(1.84)	(2.67)
Interaction		-0.41		-0.35		-0.75		-0.88
		(-5.34)		(-4.21)		(-6.47)		(-8.19)
R^2 (%)	3.36	3.47	3.46	3.54	3.02	3.40	3.12	3.73
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Reported emissions

This table reports carbon tilt coefficients and interaction terms for unanticipated climate concerns based on firms with reported emissions with t-statistics based on standard errors clustered at the factor level (in parentheses). All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Column (1) contains baseline regressions from (1). Column (2) reports interaction terms from the dynamic model in (2). Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Unanticipated climate concerns are computed as prediction errors from an ARX(1)-model for the MCCC index of Ardia et al. (2023). Panel A reports results for realized returns (RET) and Panel B reports results for forward-looking implied cost of capital (ICC) returns. Each regression is based on 24,960 factor-month observations (160 factors and 156 months). The sample period is 2010 to 2022.

	S1 Emissions		S1+2 Emissions		S1 Intensity		S1+2 Intensity	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Realized returns (RET)								
Carbon tilt	-1.54	-1.70	-1.60	-1.76	-1.02	-1.26	-1.11	-1.41
	(-6.28)	(-6.66)	(-6.33)	(-6.75)	(-4.36)	(-5.14)	(-3.83)	(-4.84)
Interaction		2.62		2.66		3.68		3.69
		(3.34)		(3.26)		(4.94)		(5.25)
R^2 (%)	2.18	2.21	2.23	2.26	1.98	2.04	2.04	2.11
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Implied cost of capital (ICC)								
Carbon tilt	0.04	0.03	0.02	0.01	0.24	0.22	0.41	0.39
	(0.72)	(0.59)	(0.37)	(0.23)	(3.91)	(3.70)	(6.05)	(5.89)
Interaction		0.15		0.15		0.30		0.27
		(3.03)		(2.97)		(6.58)		(6.97)
R^2 (%)	11.75	11.81	11.46	11.51	15.51	15.78	19.10	19.35
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Climate change exposures

This table reports carbon tilt coefficients and interaction terms for unanticipated climate concerns based on the firm-level climate change exposures from Sautner et al. (2023a) with *t*-statistics based on standard errors clustered at the factor level (in parentheses). All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Column (1) contains baseline regressions from (1). Column (2) reports interaction terms from the dynamic model in (2). Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Unanticipated climate concerns are computed as prediction errors from an ARX(1)-model for the MCCC index of Ardia et al. (2023). Panel A reports results for realized returns (RET) and Panel B reports results for forward-looking implied cost of capital (ICC) returns. Each regression is based on 24,960 factor-month observations (160 factors and 156 months). The sample period is 2010 to 2022.

	Climate change		Opportunity		Regulatory		Physical	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
Panel A: Realized returns (RET)								
Climate tilt	-0.96	-1.33	-1.02	-1.50	0.06	-0.03	0.72	0.53
	(-3.76)	(-4.49)	(-3.57)	(-4.64)	(0.20)	(-0.09)	(3.28)	(2.43)
Interaction		3.68		4.20		0.75		3.43
		(3.62)		(4.29)		(0.84)		(4.78)
R^2 (%)	3.25	3.34	3.26	3.38	3.20	3.21	3.23	3.28
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Implied cost of capital (ICC)								
Climate tilt	0.20	0.17	0.17	0.15	0.29	0.25	-0.01	-0.02
	(3.01)	(2.66)	(2.49)	(2.24)	(4.82)	(4.18)	(-0.28)	(-0.63)
Interaction		0.21		0.12		0.33		0.24
		(5.40)		(4.13)		(6.54)		(4.91)
R^2 (%)	16.16	16.33	15.77	15.83	17.66	18.11	14.79	14.93
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Group FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Figure 1: Number of firms

This figure plots the average number of U.S. firms with valid and available emission data from LSEG for each year in our sample. Emission data enter the sample at their point-in-time availability, following the approach in Zhang (2025). The sample period is 2010 to 2022.

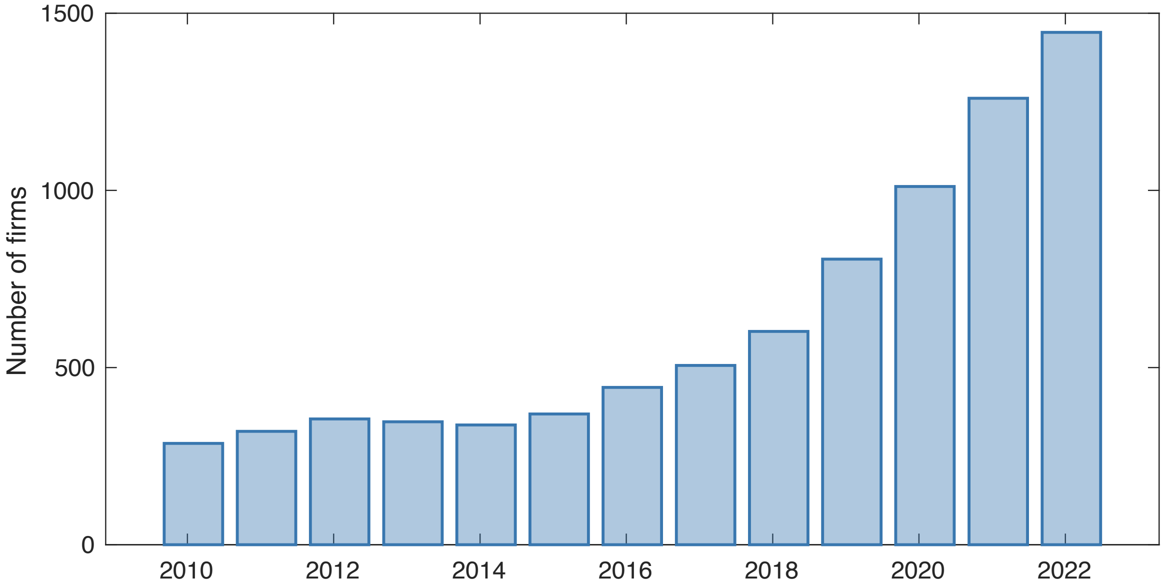

Figure 2: Average emission (intensity) over time

This figure plots the annual development in average firm-level Scope 1 and Scope 1+2 total emissions (top panel) and average Scope 1 and Scope 1+2 emission intensity (bottom panel). Total emissions are measured in megatonnes of CO2 equivalent (MtCO2e). Emission intensity is defined as MtCO2e divided by sales, scaled by 100 for readability. Gray-shaded areas are NBER recession dates. The sample period is 2010 to 2022.

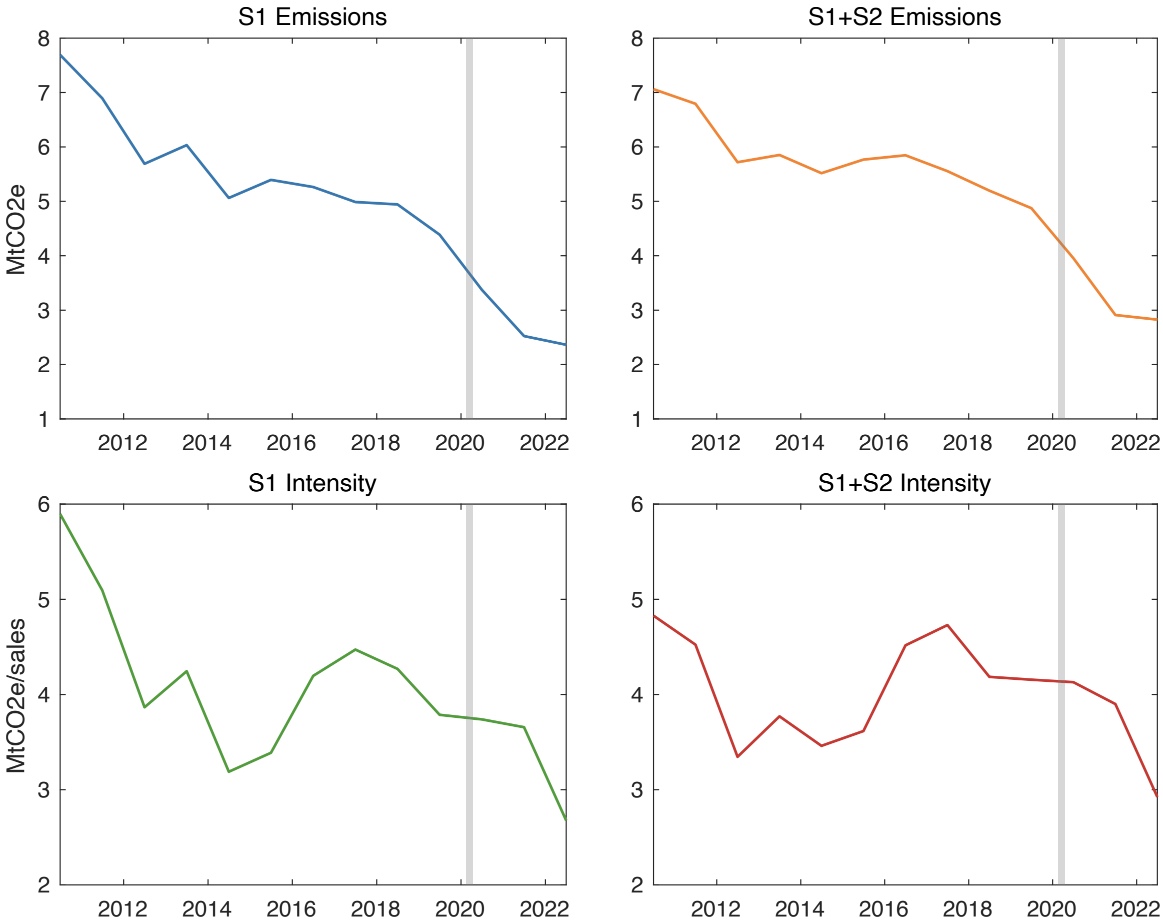

Figure 3: Descriptive statistics across factor groups

This figure plots group-level averages for expected factor returns and carbon risk across four different measures of expected return: realized excess returns (RET), implied cost of capital (ICC), Martin-Wagner (MW) lower bounds, and generalized lower bounds (GLB). Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Total emissions are measured in megatonnes of CO2 equivalent (MtCO2e). Emission intensity is defined as MtCO2e divided by sales, scaled by 100 for readability. The 160 equity factors are classified into eight groups: Earnings (12), Frictions (22), Intangibles (16), Investment (32), Momentum (22), Profitability (17), Risk (18), and Valuation (21). The sample period is 2010 to 2022.

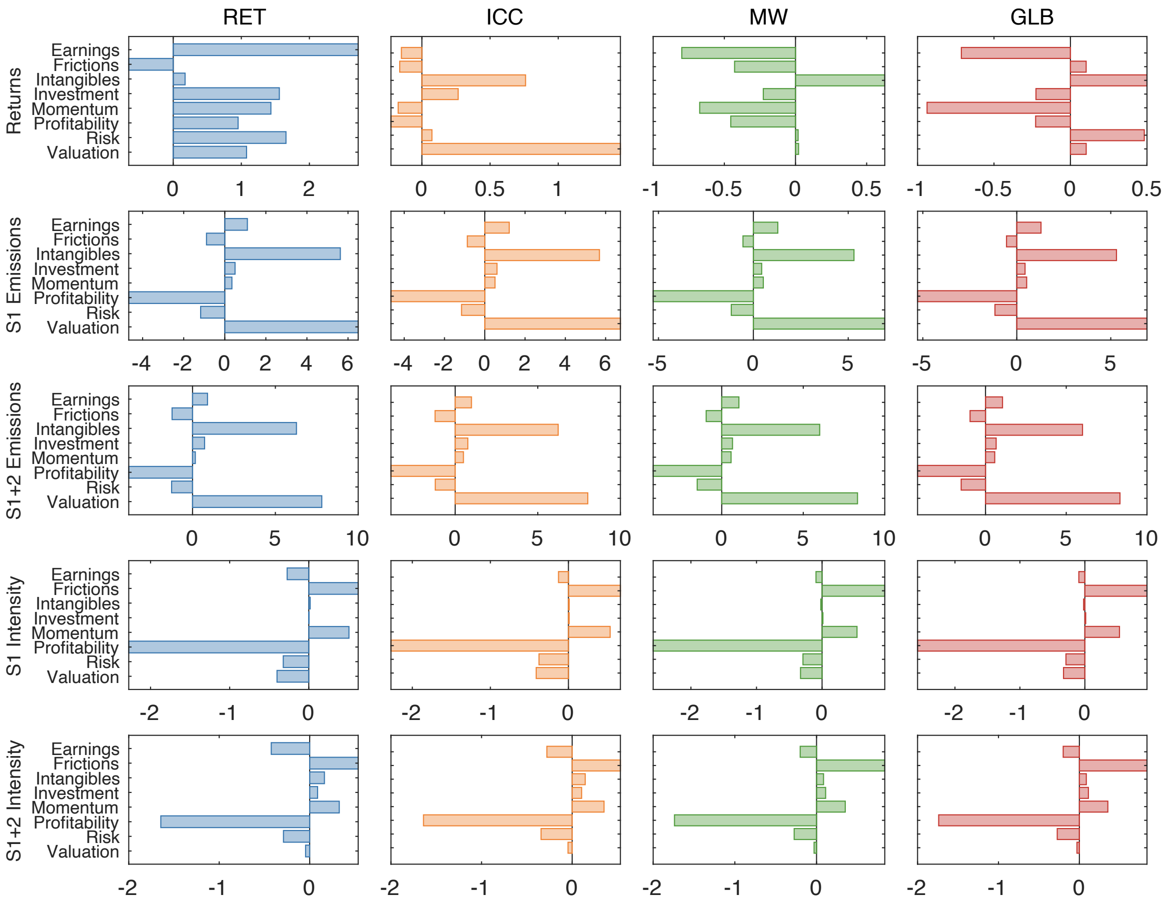

Figure 4: Rolling-window carbon tilt premia

This figure plots 36-month rolling-window carbon tilt coefficients from the regression model in (1). Statistically significant coefficients are marked by solid lines, whereas dotted lines indicate significance. t-statistics are based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. The top panel plots rolling-window carbon tilt premia for realized returns (RET), and the bottom panel reports results for forward-looking implied cost of capital (ICC) returns. Gray-shaded areas represent NBER recession dates. The sample period is 2010 to 2022.

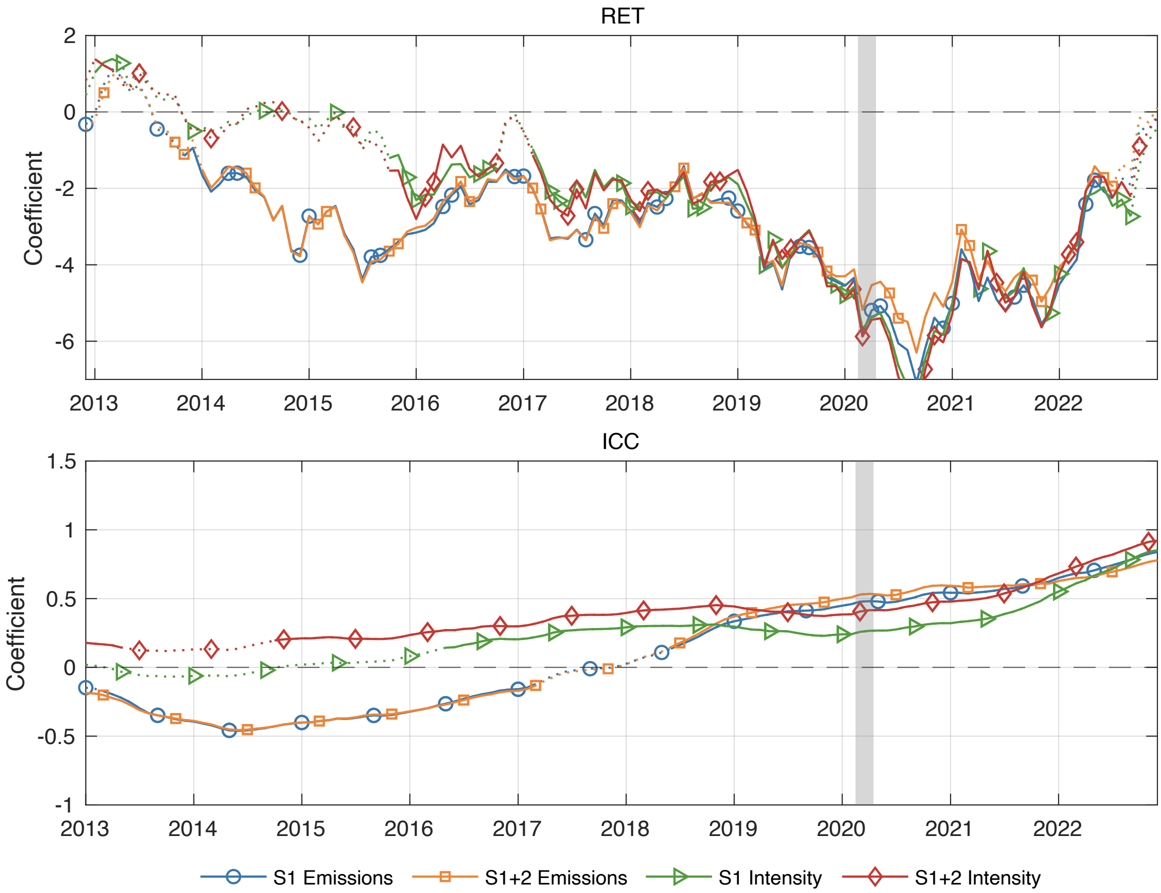

Figure 5: Carbon premium over time

This figure plots carbon tilt coefficients and interaction terms for the linear time trend from the regression model in (3) with error bars based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. The top panel reports results for realized returns (RET) and the bottom panel reports results for forward-looking implied cost of capital (ICC) returns. The sample period is 2010 to 2022.

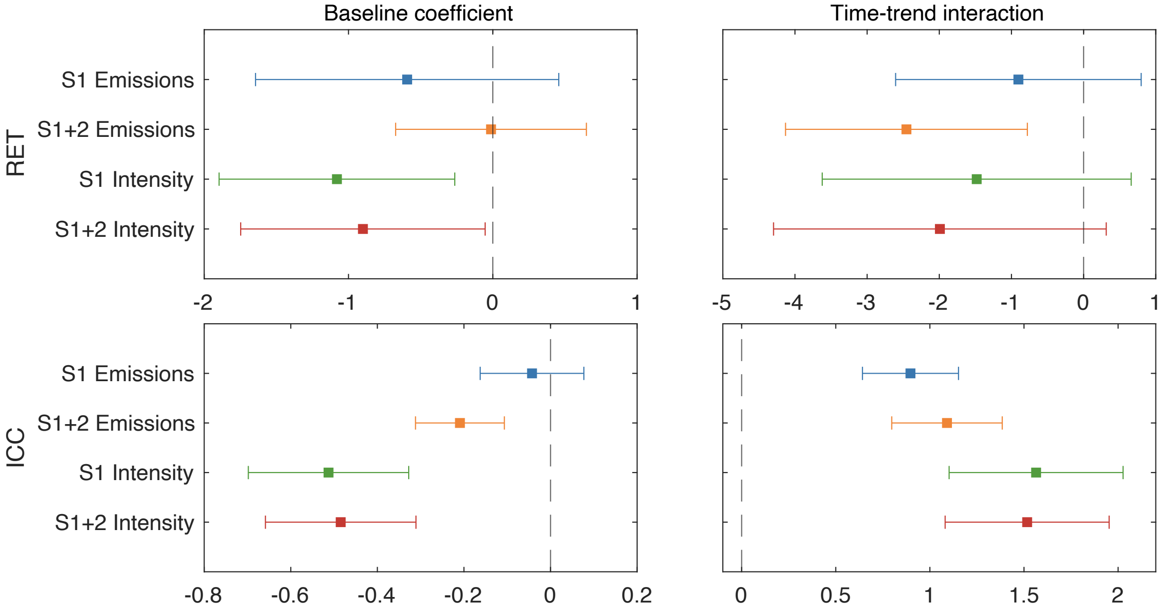

Figure 6: Carbon tilt premia across factor groups

This figure plots factor group-specific carbon tilt coefficients from the regression model in (1) with error bars based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) and year fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. The top panel reports results for realized returns (RET) and the bottom panel reports results for forward-looking implied cost of capital (ICC) returns. The 160 equity factors are classified into eight groups: Earnings (12), Frictions (22), Intangibles (16), Investment (32), Momentum (22), Profitability (17), Risk (18), and Valuation (21). The sample period is 2010 to 2022.

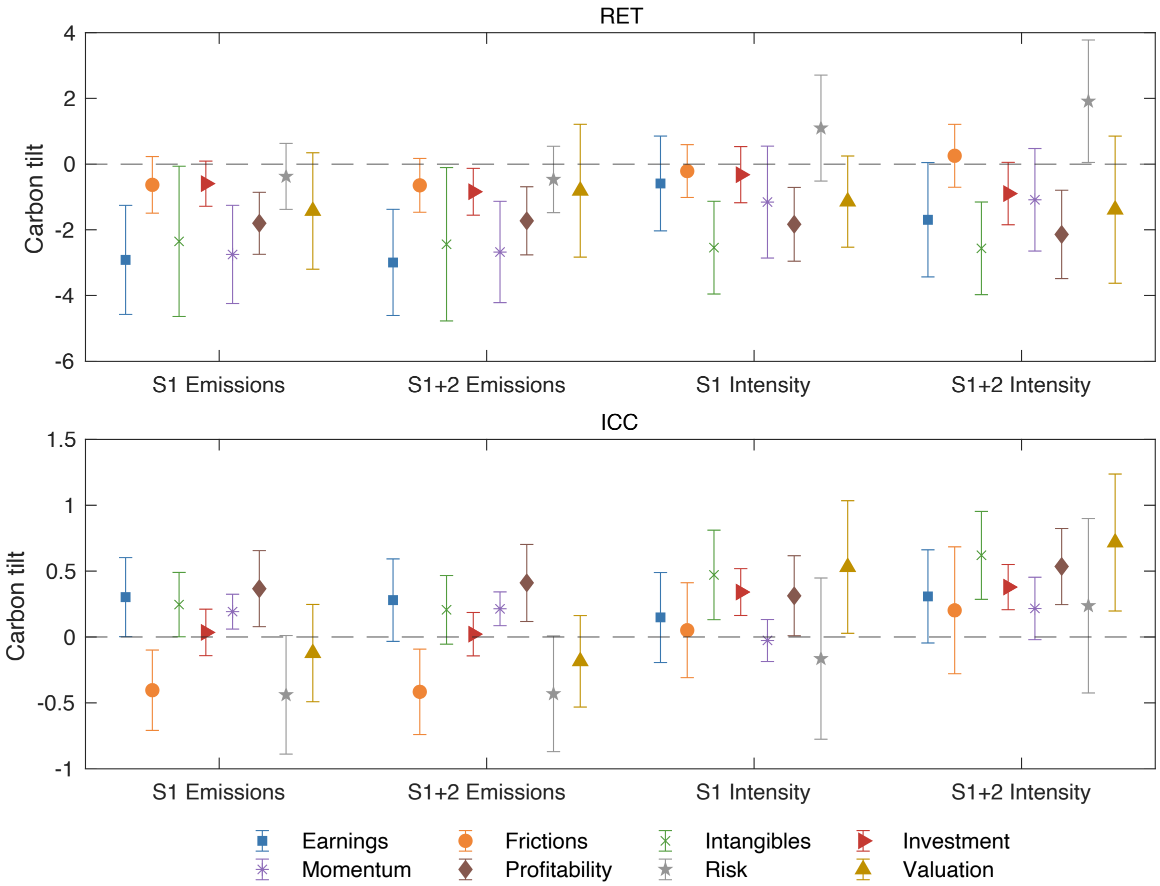

Figure 7: Interaction effects across factor groups

This figure plots factor group-specific interaction terms from the regression model in (2) with error bars based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) and year fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Unanticipated climate concerns are computed as prediction errors from an ARX(1)-model for the MCCC index of Ardia et al. (2023). The top panel reports results for realized returns (RET) and the bottom panel reports results for forward-looking implied cost of capital (ICC) returns. The 160 equity factors are classified into eight groups: Earnings (12), Frictions (22), Intangibles (16), Investment (32), Momentum (22), Profitability (17), Risk (18), and Valuation (21). The sample period is 2010 to 2022.

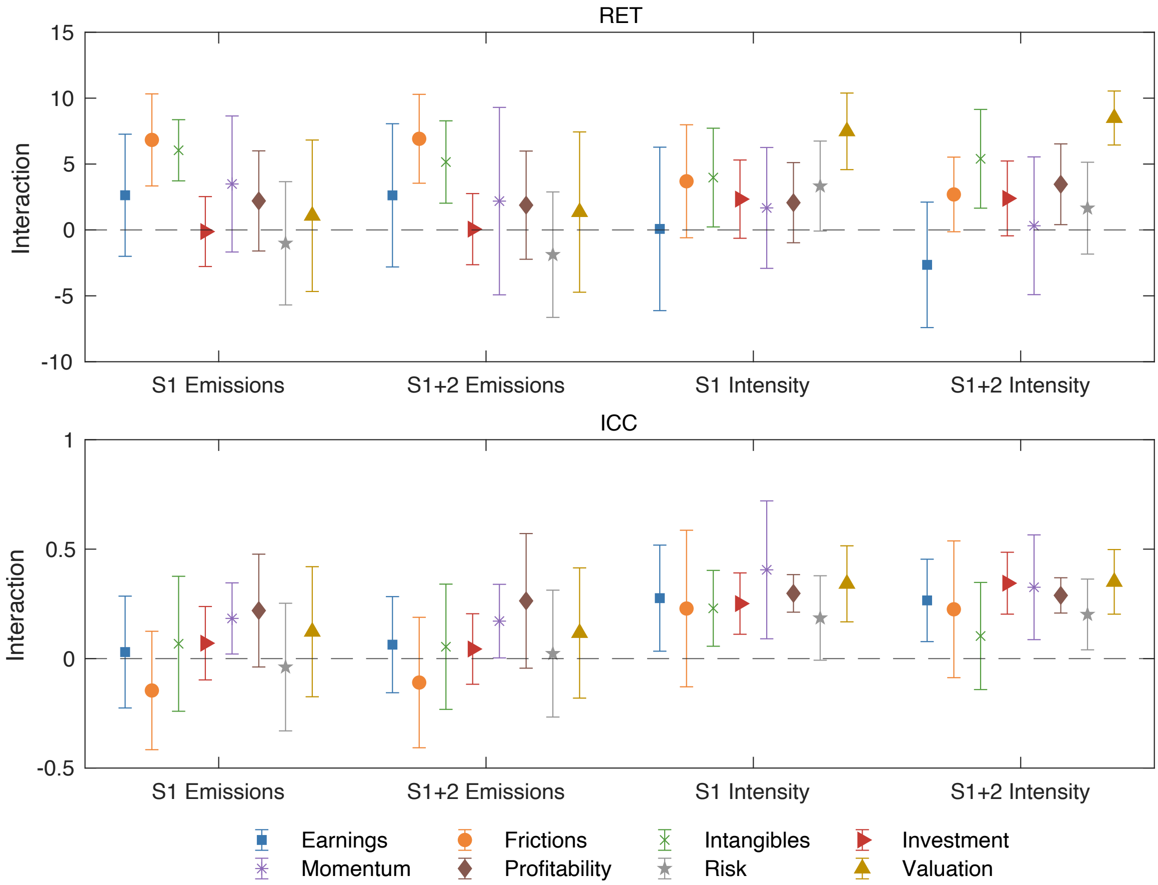

Figure 8: Rolling-window RET carbon tilt premia across groups

This figure plots 36-month rolling-window carbon tilt coefficients for realized returns (RET) from the regression model in (1). Statistically significant coefficients are marked by solid lines, whereas dotted lines indicate significance. *t*-statistics are based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) and year fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Gray-shaded areas represent NBER recession dates. The sample period is 2010 to 2022.

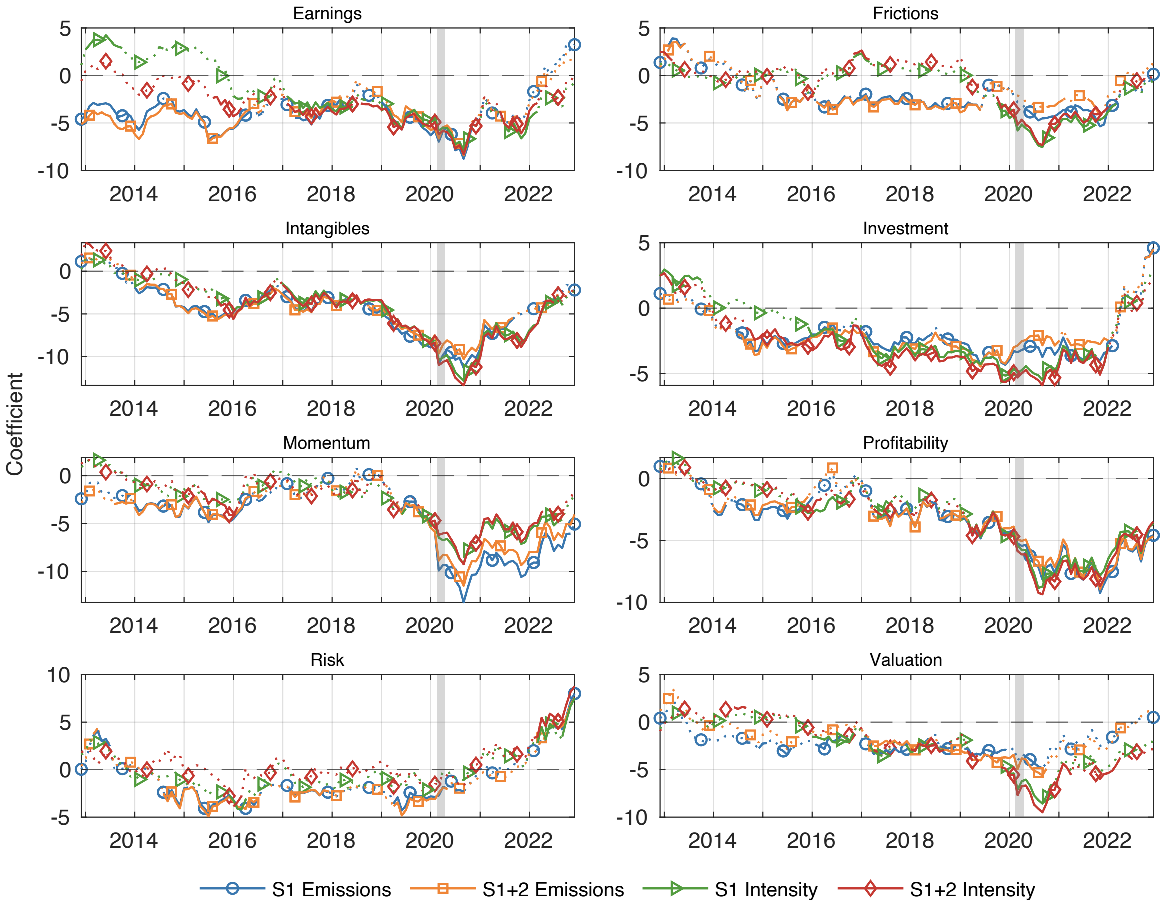

Figure 9: Rolling-window ICC carbon tilt premia across groups

This figure plots 36-month rolling-window carbon tilt coefficients for implied cost of capital (ICC) returns from the regression model in (1). Statistically significant coefficients are marked by solid lines, whereas dotted lines indicate significance. t-statistics are based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) and year fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. Gray-shaded areas represent NBER recession dates. The sample period is 2010 to 2022.

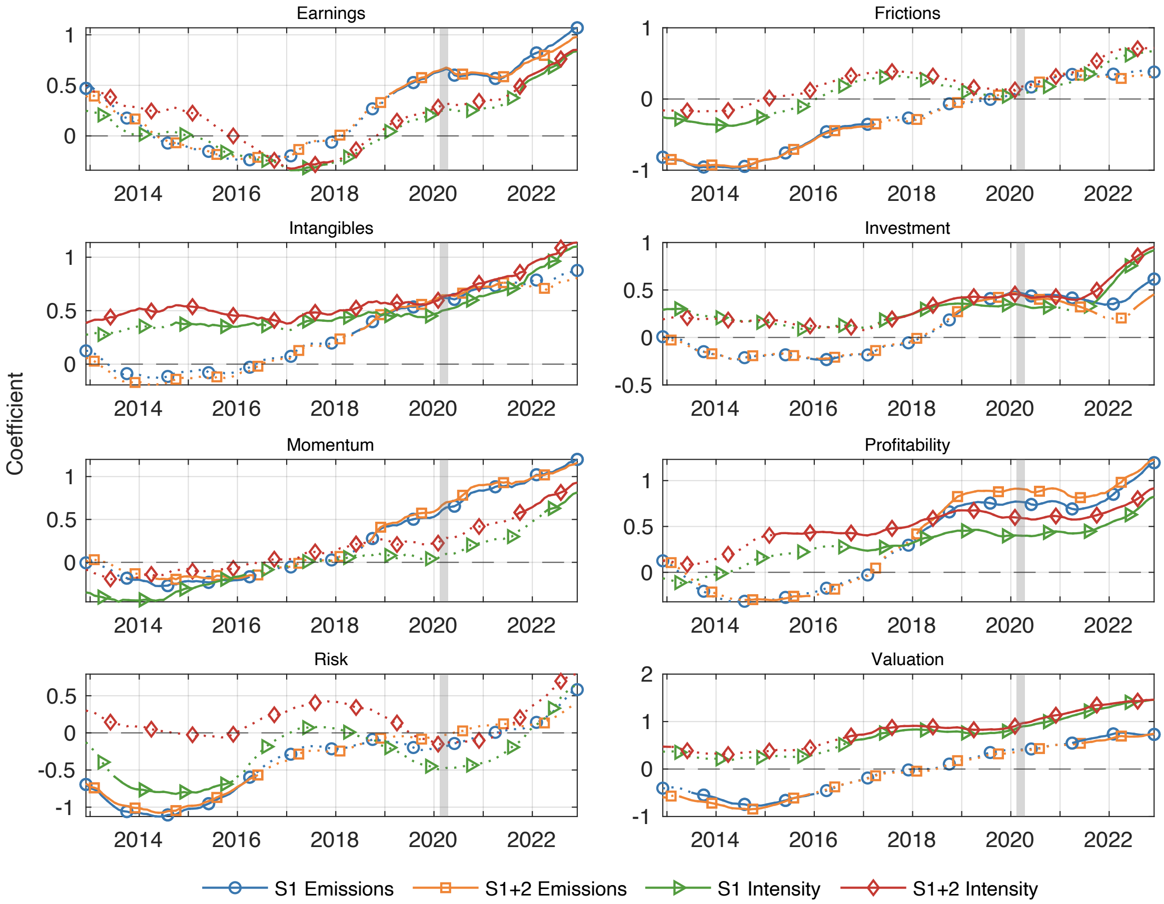

Figure 10: Option-implied carbon premium over time

This figure plots carbon tilt coefficients and interaction terms for the linear time trend from the regression model in (3) for option-implied returns. Error bars based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. The top panel reports results for Martin and Wagner (2019) (MW) returns and the bottom panel reports results for Chabi-Yo et al. (2023b) (GLB) returns. The underlying factors are constructed from S&P500 constituents. The sample period is 2010 to 2022.

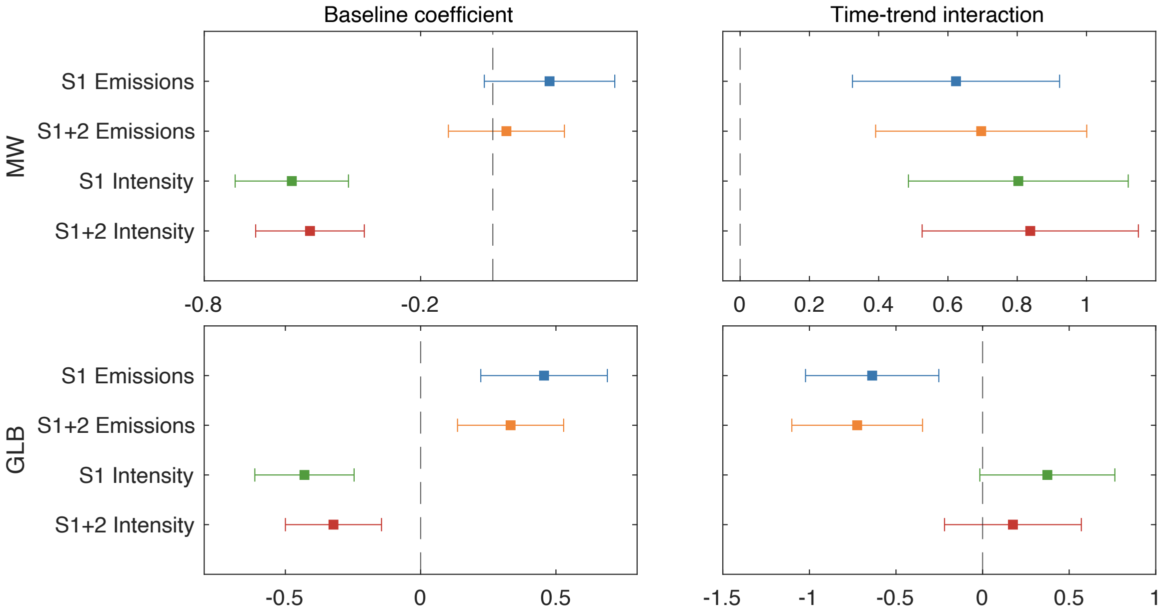

Figure 11: Fama-MacBeth regressions

This figure plots carbon tilt premia estimated using the Fama and MacBeth (1973) cross-sectional regression in (4), with error bars based on Fama-MacBeth standard errors. Carbon tilts are measured as the value-weighted difference in carbon risk between the factor's long and short legs. Carbon risk is proxied by Scope 1 and Scope 1+2 total emissions and emission intensities (emissions scaled by sales), respectively. The left panel shows results for realized returns (RET), and the right panel shows results for forward-looking implied cost of capital (ICC) returns. The sample period is 2010 to 2022.

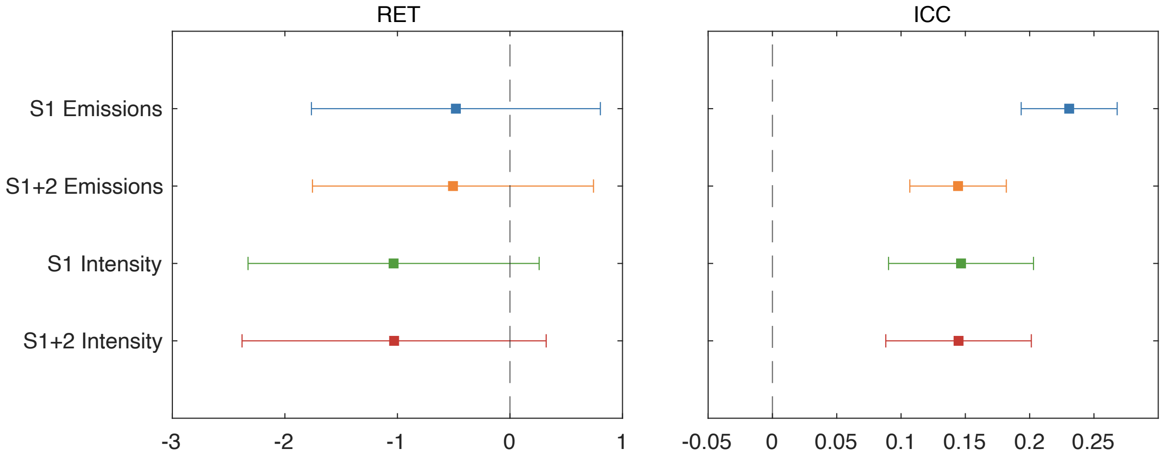

Figure 12: Carbon score regressions

This figure plots carbon tilt coefficients from the regression model in (1) (top panel), baseline and interaction terms for unanticipated climate concerns from the regression in (2) (middle panel), and initial and time-trend interaction coefficients from the time-trend model in (3) (bottom panel) based on an aggregate carbon score with error bars based on standard errors clustered at the factor level. All regressions include control variables (described in Section 2.6) together with year fixed effects and factor group fixed effects. The composite carbon score is constructed as the equal-weighted average of cross-sectionally standardized measures of Scope 1 and Scope 1+2 total emissions and emission intensities. Carbon score tilts are measured as the value-weighted difference in carbon scores between the factor's long and short legs. Each panel reports results for realized returns (RET) and implied cost of capital (ICC) returns. The sample period is 2010 to 2022.