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Non-standard errors in carbon premia

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Abstract

This research investigates the influence of methodological choices in portfolio sorts on the size of the carbon premium. By analyzing more than 100,000 methodological paths, we find that variations in the construction of brown-minus-green portfolios create substantial non-standard errors. From 2009 to 2022, the mean carbon premium is -0.16% per month, with a non-standard error of 0.26%. Additionally, there is significant time-series variation in non-standard errors, which correlates with climate media attention. Controlling for unexpected changes in climate concerns substantially reduces methodology-induced uncertainty and helps explain the absence of a consistently positive carbon premium.

JEL classification: C58, G11, G12, Q54

Keywords: non-standard errors, portfolio sorts, carbon premium, methodological uncertainty

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1 Introduction

This study revisits the carbon premium by addressing non-standard errors in the sense of Menkveld, Dreber, Holzmeister, Huber, Johannesson, Kirchler, Neusüss, Razen, Weitzel, et al. (2024). Following Walter, Weber, and Weiss (2024), we explore 116,640 methodological paths derived from 11 portfolio sort decision forks and establish an empirical distribution of the carbon premium and its test statistics in the US stock market from 2009 to 2022. We reveal that significant carbon premia are located at the tails of the distribution and that methodological choices lead to large variations in premia. Moreover, we observe time-series variation in non-standard errors and explore the economic drivers of this methodology-induced uncertainty. We conclude that it is crucial to address non-standard errors and to control for unexpected shifts in climate concerns in carbon premium research.

The impact of the transition to carbon net zero on asset prices has become a central topic in contemporary finance research. Existing studies offer differing conclusions on whether higher carbon transition risk results in higher expected returns and thus, a carbon premium. Most prominently, two studies by Bolton and Kacperczyk (2021, 2023) report a carbon premium. Other empirical studies, however, challenge this observation (e.g., Aswani, Raghunandan, and Rajgopal, 2024a; Bauer, Huber, Rudebusch, and Wilms, 2022; Cheema-Fox, LaPerla, Serafeim, Turkington, and Wang, 2021a, 2021b; Eskildsen, Ibert, Jensen, and Pedersen, 2024; Zhang, 2024). In this context, an open debate between Bolton and Kacperczyk (2024) and Aswani, Raghunandan, and Rajgopal (2024b) is focused on methodological decisions and economic interpretations. For instance, should researchers use a firm's total carbon emissions or its sales-scaled carbon intensity when quantifying firm-level carbon transition risk? And is it reasonable to assume that investors only consider reported carbon emission data or do they also rely on vendor estimates? We aim to quantify the influence of various combinations of methodological choices and to present a comprehensive picture of the carbon premium by establishing a distribution of carbon premia based on 116,640 different portfolio specifications.[1] We demonstrate that the size of the carbon premium is strongly influenced by methodological choices in the construction of portfolio sorts.

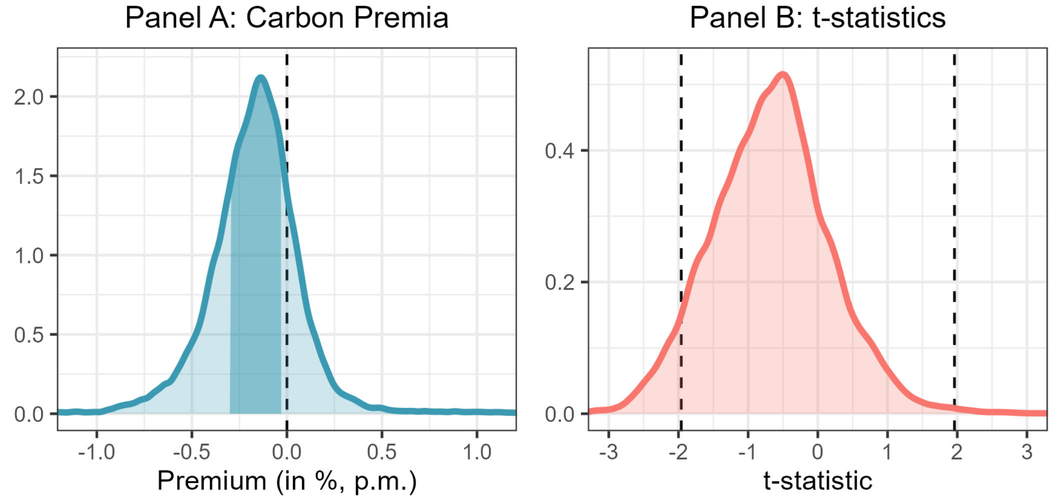
Panel A of Figure 1 illustrates the distribution of the 116,640 carbon premia[2] from 2009 to 2022. The distribution is centered around zero, with a mean return of -0.16% per month (omitting the year 2022 leads to a mean return of -0.33% per month). The 25th

[1]While the debate between Bolton and Kacperczyk (2024) and Aswani et al. (2024b) stresses the importance of methodological choices, our results are not directly comparable to theirs because of different empirical approaches (firm-level regression instead of portfolio sorts).

[2]In general, when we use the term "premium", we refer to the expected return of a portfolio that is long in stocks with high absolute carbon emissions or emission intensity (brown portfolio) and short in stocks with low absolute carbon emissions or emission intensity (green portfolio). We additionally calculate risk-adjusted carbon premia based on various asset pricing models.

Figure 1: Distribution of Carbon Premia

Panel A of this figure shows the distribution of carbon premia resulting from different methodological choices in portfolio construction described in Table 2. **Panel B** shows the distribution of the corresponding t-statistics.

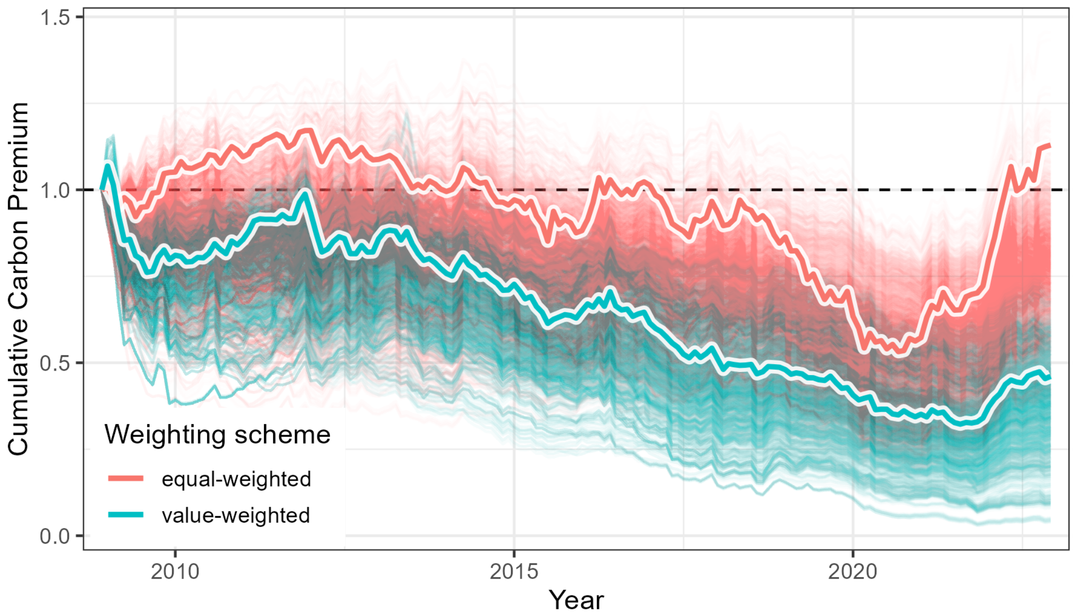


percentile return is -0.30% and the 75th percentile return is -0.03%. Thus, the interquartile range of carbon premia, which quantifies the size of the non-standard error, is 0.26% per month. Panel B shows that most carbon premia are statistically indistinguishable from zero, but the variation across specifications yields both negative and positive statistically significant carbon premia at the tails. While 6% of all carbon premia are negative and statistically significant, less than 1% of portfolio specifications yield a positive and statistically significant carbon premium.

To demonstrate the significant impact of small methodological changes on carbon premia, Figure 2 displays the cumulative carbon premia of two brown-minus-green (BMG) portfolios sorted by scope 1 emissions from 2009 to 2022. Both portfolios are long in stocks with high absolute carbon emissions and short in stocks with low absolute carbon emissions. The only difference between the two identically constructed portfolios is the weighting scheme. Portfolio A (red line) is equal-weighted, while Portfolio B (blue line) is value-weighted. This single methodological variation results in a cumulative carbon premium that is either slightly positive or strongly negative, with a time-series correlation of only 0.55.

The blurred lines in Figure 2 represent cumulative carbon premia for all possible portfolio specifications conditional on the weighting scheme. Studying the distributions of carbon premia between decision forks allows for an evaluation of the uncertainty induced by the fork under investigation. Our analyses indicate that carbon premia are significantly influenced not only by the weighting scheme but also by other methodological choices, such as the number of portfolio breakpoints and size as well as industry adjustments. The most critical decision pertains to the carbon transition risk proxy used for sorting the portfolios. When focusing on corporate carbon emissions, both the scope considered

Figure 2: Cumulative Carbon Premia Conditional on Weighting Scheme
This figure shows cumulative carbon premia resulting from different methodological choices in portfolio construction over the 2009 to 2022 period. Equal-weighted BMG portfolio returns are plotted in red and value-weighted returns are plotted in blue. The two bold lines illustrate cumulative returns of a pair of scope 1 emission-sorted BMG portfolios that are constructed in exactly the same way but differ in their weighting scheme.



and the implementation method (i.e., absolute carbon emissions versus emission intensity) strongly affect carbon premia. Additionally, incorporating vendor-estimated carbon emissions adds to methodological uncertainty. To address concerns that carbon emissions may not fully capture firms' carbon transition risk, we also explore firm-level climate change exposure variables proposed by Sautner, van Lent, Vilkov, and Zhang (2023a) as alternative sorting variables.

As non-standard errors in carbon premia prove to be relevant, we continue to investigate the underlying economic drivers and link the time-series of non-standard errors to explanations for return differences between green and brown stocks as modeled by Pástor, Stambaugh, and Taylor (2021). In their model, brown stocks are expected to earn higher returns because (i) these stocks bear higher risk and (ii) investors have non-pecuniary preferences for holding green stocks. However, this expected return relation reverses if investors' preferences for green stocks strengthen unexpectedly, leading to higher demand for green stocks and repricing effects. Ardia, Bluteau, Boudt, and Inghelbrecht (2023) proxy such periods of unexpected changes in environmental preferences by an index of climate media attention based on major US newspapers. Both Ardia et al. (2023) and Pástor, Stambaugh, and Taylor (2022) find that green stocks tend to outperform brown stocks in periods when the climate media attention is high. Our results largely confirm this relation and further show that the time-series of non-standard errors in carbon premia is correlated to climate media attention. This indicates phases of a negative carbon premium characterized by low methodological uncertainty when climate concerns increase unexpectedly.

This study makes several contributions. First, it is related to a rapidly growing literature on the pricing of environmental risks in the stock market. Several equilibrium models suggest a negative relation between a firm's corporate environmental performance and its expected stock returns (e.g., Heinkel, Kraus, and Zechner, 2001; Pástor et al., 2021; Pedersen, Fitzgibbons, and Pomorski, 2021; Zerbib, 2022). Empirical studies provide a less clear picture and show mixed results. Bolton and Kacperczyk (2021, 2023) find that stocks of firms with higher total carbon emissions earn higher returns. Aswani et al. (2024a) challenge this finding and suggest that Bolton and Kacperczyk's (2021) carbon premium is driven by using absolute emissions instead of emission intensities, biased carbon emission vendor estimates, and inappropriate size adjustments. Using portfolio sorts based on firms' carbon performance, Cheema-Fox et al. (2021a, 2021b), Eskildsen et al. (2024), Goergen, Nerlinger, and Wilkens (2020), and Zhang (2024) do not find a statistically significant carbon premium or even indicate that portfolios with green stocks earn significantly higher (risk-adjusted) returns than portfolios with brown stocks. Additionally, Zhang (2024) emphasizes the role of firm fundamentals and lagged carbon emissions to avoid a potential look-ahead bias. Atilgan, Demirtas, Edmans, and Gunaydin (2023) suggest that a large part of the carbon premium is due to mispricing instead of risk, as reflected in abnormal earnings announcement returns. We reconcile these contradictory results by establishing an empirical distribution of carbon premia based on 116,640 methodological paths that shows that the carbon premium is centered around zero.

Second, we confirm the results of Ardia et al. (2023) and Pástor et al. (2022), who relate time-series variation in green stock returns to unexpected shifts in climate concerns and find that green stocks outperform brown stocks when investors' preferences for green stocks strengthen unexpectedly. This also relates to an earlier contribution of Engle, Giglio, Kelly, Lee, and Stroebel (2020), who propose a hedging strategy building on climate change media attention. Our results suggest that a potential carbon premium might be masked by unexpectedly increasing preferences of investors for low-carbon stocks. Moreover, in such times, the methodology-induced uncertainty in the carbon premium decreases, stressing the importance of controlling for changes in climate change concerns in carbon premium research.

Finally, methodologically, this paper contributes to the literature on non-standard errors – a term introduced by Menkveld et al. (2024) to describe the variation in empirical results caused by researchers' methodological decisions. While prior literature uses different approaches to quantify the carbon premium, this study concentrates on methodological variation in a rather standardized procedure in asset pricing, namely portfolio sorts. Following Walter et al. (2024), we investigate the impact of multiple methodological decisions and show the entire distribution of carbon premia. We adapt their methodology to a new setting and introduce new forks and choices that are relevant in the context of the carbon premium. We also add to the "replication crisis" literature (e.g., Chen and Zimmermann, 2022; Hasler, 2023; Hou, Xue, and Zhang, 2020; Jensen, Kelly, and Pedersen, 2023) and show that the range of published results on the carbon premium can be reproduced.

The remainder of this paper is organized as follows. Section 2 describes the data and methodology. Section 3 presents the distribution of carbon premia caused by differing methodological choices and analyzes which choices have the greatest impact on carbon premia. Section 4 investigates economic drivers of the time-series variation in non-standard errors. Section 5 concludes.

2 Data and Methodology

2.1 Data

This study covers US common stocks traded at the NYSE, NYSE American (formerly AMEX), or NASDAQ over the 2009 to 2022 period. Monthly data on stock prices, returns, number of shares outstanding, and SIC industry classification come from CRSP. Delisting returns are adjusted following Shumway (1997). Asset pricing model factors are downloaded from Kenneth French's and Kewei Hou et al.'s websites.[3]

The carbon emission data come from MSCI and Refinitiv and comprise reported scope 1, scope 2, and scope 3 emissions. For each scope, we consider total emissions in tons of CO_2-equivalent emissions and the sales-scaled emission intensity. For the analysis in section 3.2, we additionally consider the combined reported scope 1+2 emissions as well as scope 1+2 emissions estimated by Refinitiv and MSCI. The sample size and period are mainly restricted by the availability of carbon emission data from both vendors. Summary statistics are presented in Table 1.

Table 1 demonstrates that MSCI and Refinitiv provide similar firm coverage regarding reported carbon emissions. However, MSCI initially provides estimated carbon emissions for a significantly higher number of firms, whereas Refinitiv offers estimates for more firms in the latter half of the investigation period. Analyzing the trends of reported emissions over time reveals that the average firm's scope 1 emissions (direct emissions from sources owned or controlled by a firm) and scope 2 emissions (indirect emissions from the consumption of purchased electricity, heat, or steam) are decreasing sharply. In contrast, scope 3 emissions (indirect emissions occurring in a firm's value chain, such as those from the production of purchased materials, product use, and waste disposal) are increasing strongly.[4] Please note that these trends may only reflect an increasing coverage

[3] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
https://global-q.org/factors.html

[4] We illustrate only the reported emissions from Refinitiv, as Busch, Johnson, and Pioch (2022) indicate

Table 1: Summary Statistics

This table reports summary statistics for the carbon emission data per year and data vendor. $N_{Reported}$ gives the number of firms with reported emission data for any scope and $N_{Estimated}$ gives the number of firms with estimated scope 1+2 emission data only. The columns *Scope 1*, *Scope 2*, and *Scopes 3* show the cross-sectional average of reported CO_2-equivalent emissions in tons per scope.

	MSCI		Refinitiv				
Year	N_{Reported}	$N_{\text{Estimated}}$	N_{Reported}	$N_{\text{Estimated}}$	Scope 1	Scope 2	Scope 3
2008	145	1,011	170	474	9,451,871	1,478,058	341,451
2009	224	962	236	560	7,016,788	941,410	4,204,926
2010	262	951	316	537	5,723,596	982,587	6,482,828
2011	293	947	341	529	5,237,812	870,229	9,017,811
2012	310	974	378	501	4,868,621	865,125	10,130,521
2013	331	1,014	385	494	4,239,463	845,776	9,909,300
2014	350	1,074	354	520	4,387,680	909,295	10,190,629
2015	374	1,130	365	669	4,653,231	876,913	10,495,161
2016	411	1,162	411	1,217	4,196,736	856,014	9,298,230
2017	454	1,214	478	1,830	4,141,782	890,296	10,634,472
2018	534	1,213	552	2,042	3,981,023	803,140	13,512,887
2019	691	1,127	678	2,063	3,169,856	617,600	12,128,024
2020	791	1,121	828	2,050	2,690,197	493,701	14,373,164
2021	722	1,326	930	2,037	2,131,392	398,400	14,140,155
2022	929	946	967	1,862	2,115,216	372,752	20,759,238

of smaller firms with lower (or higher) absolute scope 1 and scope 2 (or scope 3) carbon emissions.

As an alternative measure of carbon risk in section 3.3, we use the firm-level climate change exposure variables developed by Sautner et al. (2023a) and accessible via their website.[5] The proxy for climate media attention used in section 4 is the updated version of the monthly Media Climate Change Concerns (MCCC) index of Ardia et al. (2023), accessible via the authors' post on Sentometrics.[6]

2.2 Decision Forks in BMG Portfolio Construction

Researchers have to make multiple decisions when implementing portfolio sorts. This results in literally thousands of options on how to construct long-short portfolios. Following the terminology of Menkveld et al. (2024), we refer to any decision to be made as a "fork" that has a specified set of choices. Each possible combination of choices is called a "path". We distinguish between forks and choices used in our main model and those used in supplementary analyses. The rationale is that all forks and choices in our main model

that reported scope 1 and scope 2 emissions from different vendors have a correlation of approximately 98%.

[5] https://doi.org/10.17605/OSF.IO/FD6JQ

[6] https://sentometrics-research.com/download/mccc/

are mutually compatible, whereas this is not the case for the alternative and additional forks and choices.

Our main model includes 11 forks with a total of 34 choices, resulting in 116,640 distinct paths for constructing BMG portfolios. An overview is provided in Table 2 Panel A. The first two methodological decisions to be made concern the sorting variable, forks 3 to 6 are about sample selection, and forks 7 to 11 are about portfolio construction and premium calculation. Some of the forks seem more relevant with respect to constructing BMG portfolios, while other forks are motivated by common procedures established in other areas of the asset pricing literature.[7]

Panel B of Table 2 shows the alternative and additional forks and choices. First, as an alternative measure of carbon transition risk, we use the firm-level climate change exposure variables developed by Sautner et al. (2023a). We exclude these sorting variable choices from our main analysis because they necessitate major modifications to fork 8 (portfolio breakpoints) and fork 10 (weighting scheme). A more detailed explanation can be found in section 3.3. Second, we consider the inclusion of vendor carbon emission estimates as an additional fork. This fork is excluded from our main analysis because Refinitiv only provides information on the collection procedure for combined scope 1 and 2 emissions, limiting fork 1 (sorting variable) to aggregated scope 1 and 2 emissions. Finally, we consider the sample period as an additional fork. In the main analysis, the sample period is held fixed and non-standard errors in carbon premia are investigated over the entire 2009 to 2022 sample period. As there is large time-series variation in carbon premia, we separately examine the influence of researchers' choices about the sample period in section 3.4.

Of course, this list of forks and choice sets could be further extended. Walter et al. (2024) consider up to 14 forks that have been utilized differently in prior literature. However, to keep the number of possible specifications within reasonable limits, we restrict our analysis to the forks mentioned above, which seem most relevant in the context of carbon premia calculation. Consequently, the results can be interpreted as the lower bound of non-standard errors.

2.3 Empirical Methodology

Based on the previously described paths, we build BMG portfolios which are long in the portfolio with the highest carbon emissions (intensity) and short in the portfolio with the lowest carbon emissions (intensity). For each BMG portfolio path p, we then calculate the time-series mean raw return and factor-adjusted premia. Equation (1) describes this

[7] See Walter et al. (2024) for a discussion of which decision forks have been used in the asset pricing literature and an evaluation of the relative weighting of choices per fork.

Table 2: Forks and Choices in BMG Portfolio Construction

This table provides an overview of the forks and choices in BMG portfolio construction. N gives the number of possibles choices per fork and the total number of paths results from the combination of all possible choices. **Panel A** reports the forks and choices used in the main model. **Panel B** presents alternative and additional forks and choices used in supplementary analyses.

Decision Forks	Possible Choices	Construction Details	N
		Panel A: Main Model Forks and Choices	
1. Sorting variable	scope 1, scope 1 intensity, scope 2, scope 2 intensity, scope 3, scope 3 intensity	Reported total and sales-scaled CO_2-equivalent emissions per scope.	6
2. Data vendor	Refinitiv, MSCI	Data vendor providing firm-level carbon emission data.	2
3. Size exclusion	none, 10%, 20%	Exclusion of small stocks identified by NYSE market capitalization percentiles.	3
4. Exclusion of financials	yes, no	Exclusion of financial firms identified by SIC codes between 6000 and 6999.	2
5. Exclusion of utilities	yes, no	Exclusion of utilities identified by SIC codes between 4900 and 4999.	2
6. Penny stock exclusion	none, \$5, \$1	Exclusion of penny stocks below thresholds identified by their year-end share price.	3
7. Sorting variable lag	same year, next year, next year + 6 months lag	Defines the lag of sorting variables to stock returns. As carbon emissions are usually updated annually, the lag controls for a possible look-ahead bias.	3
8. Number of portfolios	2, 3, 4, 5, 10	Defines the number of quantiles.	5
9. Double sorting	none, size, industry	"none" refers to a single sort. "size" ("industry") refers to a dependent double sort with first order sorting variable market capitalization quintiles (one-digit SIC codes).	3
10. Weighting scheme	equal-weighted, value-weighted, emission-weighted	Defines weighting scheme of portfolio returns. "emission-weighted" gives more weight to firms with high (low) emissions in the long (short) portfolio.	3
11. Rebalancing	annually, monthly	For annual rebalancing, the month of the rebalancing depends on the sorting variable lag and is end of December for the same and next year match and end of June for the variant including 6 months reporting lag.	2
Total number of paths			116,640
		Panel B: Alternative and Additional Forks and Choices	
1b. Sorting variable	$CC_{Exposure}$, $CC^{Reg}_{Exposure}$, CC_{Risk}, CC^{Reg}_{Risk}	Variants of the firm-level climate change exposure introduced by Sautner et al. (2023a) as an alternative measure of carbon transition risk.	4
12. Include vendor estimates	yes, no	Inclusion of carbon emission estimates from the data vendor selected in fork no. 2.	2
13. Sample period	any period between 2008 and 2022	Select an annual (January to December) sample period. We require a minimum sample period of 3 years.	78

approach for raw returns:

$$r_p = \frac{1}{T}\sum_{t=1}^{T}(r_{t,p}^{brown} - r_{t,p}^{green}). \tag{1}$$

Specifically, we calculate alphas from the CAPM, Fama and French (1993) 3-factor model (FF3), Carhart (1997) 4-factor model (FF4), Fama and French (2015) 5-factor model (FF5), and Hou, Mo, Xue, and Zhang (2021) q-factor model (q5). The corresponding t-statistics are calculated using Newey and West (1987) standard errors with automatic lag selection as in Newey and West (1994). We keep the procedure for calculating standard errors constant in order to obtain comparable results. However, it should be noted that changes in the adjustments to the t-statistics could further influence the carbon premia in terms of statistical significance. Finally, we arrive at 116,640 carbon premia with corresponding test statistics as shown in Figure 1.

To get an aggregated impression of the importance of methodological choices on the size of the carbon premium, we calculate non-standard errors. Non-standard errors are defined according to Menkveld et al. (2024) as the interquartile range of carbon premia across paths. Equation (2) describes this approach for raw returns:

$$NSE = Q_{0.75}(r) - Q_{0.25}(r). \tag{2}$$

As in Menkveld et al. (2024), we assess the significance of non-standard errors by testing whether any of the carbon premia differ significantly from the median premium across all paths. In addition, we report the relative frequency of these significantly different carbon premia on both sides of the distribution.

To evaluate which forks induce the largest variation in carbon premia, we follow Walter et al. (2024) and calculate the mean absolute difference (MAD) for each fork f and month t as:

$$MAD_t^f = \frac{1}{|S_f|}\sum_{(i,j)\in S_f} |r_{t,i} - r_{t,j}|, \tag{3}$$

where S_f defines a set of unique pairs of paths (i, j) that only differ in the choice made at fork f. Aggregated across time, MAD^f gives the time-series average of MAD_t^f and allows to quantify the impact of a specific fork f on carbon premia.

3 Methodological Uncertainty in Carbon Premia

This section investigates methodological uncertainty in the construction of BMG portfolios. To measure methodological uncertainty, we rely on non-standard errors in the sense of Menkveld et al. (2024). Non-standard errors are errors arising due to the variation in researchers' methodological choices (Menkveld et al., 2024). The term "error" does not mean that some choices are wrong, but emphasizes the fact that these choices can lead to inconsistent results. To illustrate non-standard errors in BMG portfolio construction with respect to carbon emissions, Figure 3 plots the distribution of carbon premia for raw returns and factor-adjusted premia. It is obvious that the carbon premia vary widely across paths and that they are centered around zero.

Figure 3: Distribution of Carbon Premia Across Asset-Pricing Models
This figure shows the distribution of carbon premia (mean raw returns and factor-adjusted premia) resulting from different methodological choices in portfolio construction described in Table 2.

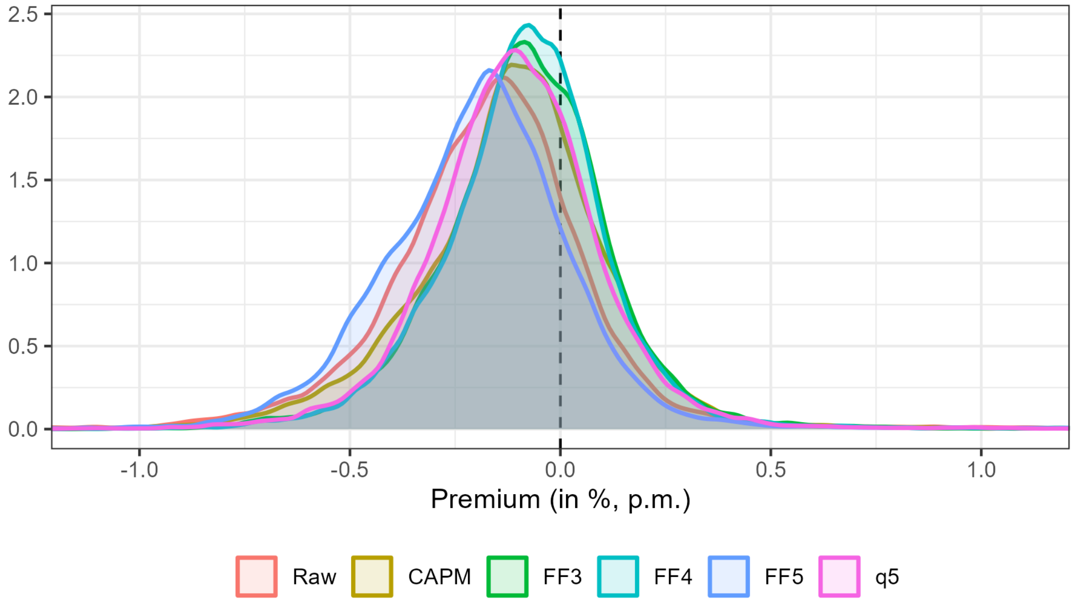


Table 3 provides statistics of the distributions of the carbon premia. For the raw return, the mean carbon premium is -0.16%, with 6% of the carbon premia being negative and statistically significant (column "Neg") and less than 1% of the premia being positive and statistically significant (column "Pos"). Adjusting the raw returns using factor models shifts the distribution to the right for the CAPM, FF3, FF4, and q5 models. Adjusting the raw return by the market factor reveals that the BMG portfolios exhibit significant exposure to the market return. The mean carbon premium increases from -0.16% to -0.11%. Moreover, adding a size and a value factor to the CAPM leads to a mean carbon premium of -0.08%. However, no more than 1% of the carbon premia are positive and statistically significant. Adding the momentum factor to the FF3 model does not change the mean carbon premium, indicating that the BMG portfolios do not have an exposure to the momentum factor, on average. Notably, implementing the FF5 model, which includes profitability and investment factors, shifts the distribution to the left, resulting in a mean carbon premium of -0.19%. Here, 17% of the carbon premia are negative and statistically significant. These findings corroborate the insights of Zhang (2024), indicating that BMG portfolios significantly load on profitability and investment factors.

Regarding methodological uncertainty, it is clear that adjusting raw returns by common risk factors does not significantly reduce uncertainty. The FF4 model achieves the greatest reduction, decreasing the average monthly non-standard error from 0.26% to 0.23%, an approximate reduction of 11%. Additionally, the "Left-right" column highlights the significance of non-standard errors by testing whether any of the carbon premia significantly differ from the median carbon premium across all paths. It reports the relative frequency of these significantly different carbon premia on both sides of the median. For raw returns and all factor-adjusted premia, some carbon premia significantly deviate from the median on both sides of the distribution, indicating that non-standard errors are statistically significant. Notably, the proportion of significant deviations to the right is higher than to the left, suggesting more extreme positive carbon premia.

Table 3: Non-Standard Errors Across Asset-Pricing Models

This table reports summary statistics for BMG portfolio raw returns and factor-adjusted carbon premia in % per month. Non-standard errors (*NSE*) are defined as the interquartile range of carbon premia resulting from different choices in portfolio construction described in Table 2. *Left-right* denotes the proportion of significant deviations to the left and right of the median carbon premium using a 5% significance level. Columns *Pos* and *Neg* indicate the proportion of positive and negative statistically significant carbon premia at the 5% level.

Model	Mean	p25	p75	NSE	Left-right	Pos	Neg
Raw	-0.16	-0.30	-0.03	0.26	(0.01, 0.02)	0.00	0.06
CAPM	-0.11	-0.24	0.02	0.26	(0.00, 0.03)	0.01	0.01
FF3	-0.08	-0.20	0.04	0.24	(0.01, 0.03)	0.01	0.04
FF4	-0.08	-0.20	0.03	0.23	(0.01, 0.02)	0.01	0.04
FF5	-0.19	-0.33	-0.06	0.27	(0.02, 0.06)	0.00	0.17
q5	-0.10	-0.23	0.01	0.24	(0.02, 0.03)	0.01	0.07

To interpret the size of the non-standard errors, we benchmark them against the average non-standard error in premia across 68 distinct factor sorting variables as reported by Walter et al. (2024). Compared to the average non-standard error of 0.19% per month reported by Walter et al. (2024), the average monthly non-standard error in carbon premia is approximately 37% larger.

3.1 Impact of Decision Forks

This section investigates which of the 11 forks in BMG portfolio construction induces the largest variation in carbon premia. The impact of a specific fork on carbon premia can be quantified by the time-series average MAD as defined in equation (3). This value gives the mean absolute difference in premia between paths that only differ in one specific fork. Results are presented in Table 4 and reveal substantial heterogeneity in the impact of forks on carbon premia.

The largest impact on carbon premia comes from the chosen sorting variable. The time-series average MAD for this fork is 2.45 percentage points per month. Thus, researchers can come to very different conclusions conditional on the carbon transition risk

Table 4: Mean Absolute Differences in Carbon Premia Across Forks

This table reports the time-series mean absolute difference (MAD) in carbon premia conditional on the choice in a specific fork. MAD is defined as in equation (3) and given in % per month. The forks are arranged in descending order of MAD.

Decision Fork	MAD
Sorting variable	2.45
Weighting scheme	2.16
Data vendor	1.51
Double sorting	1.48
Number of portfolios	1.30
Sorting variable lag	1.07
Exclusion of utilities	0.89
Exclusion of financials	0.82
Rebalancing	0.23
Penny stock exclusion	0.19
Size exclusion	0.17

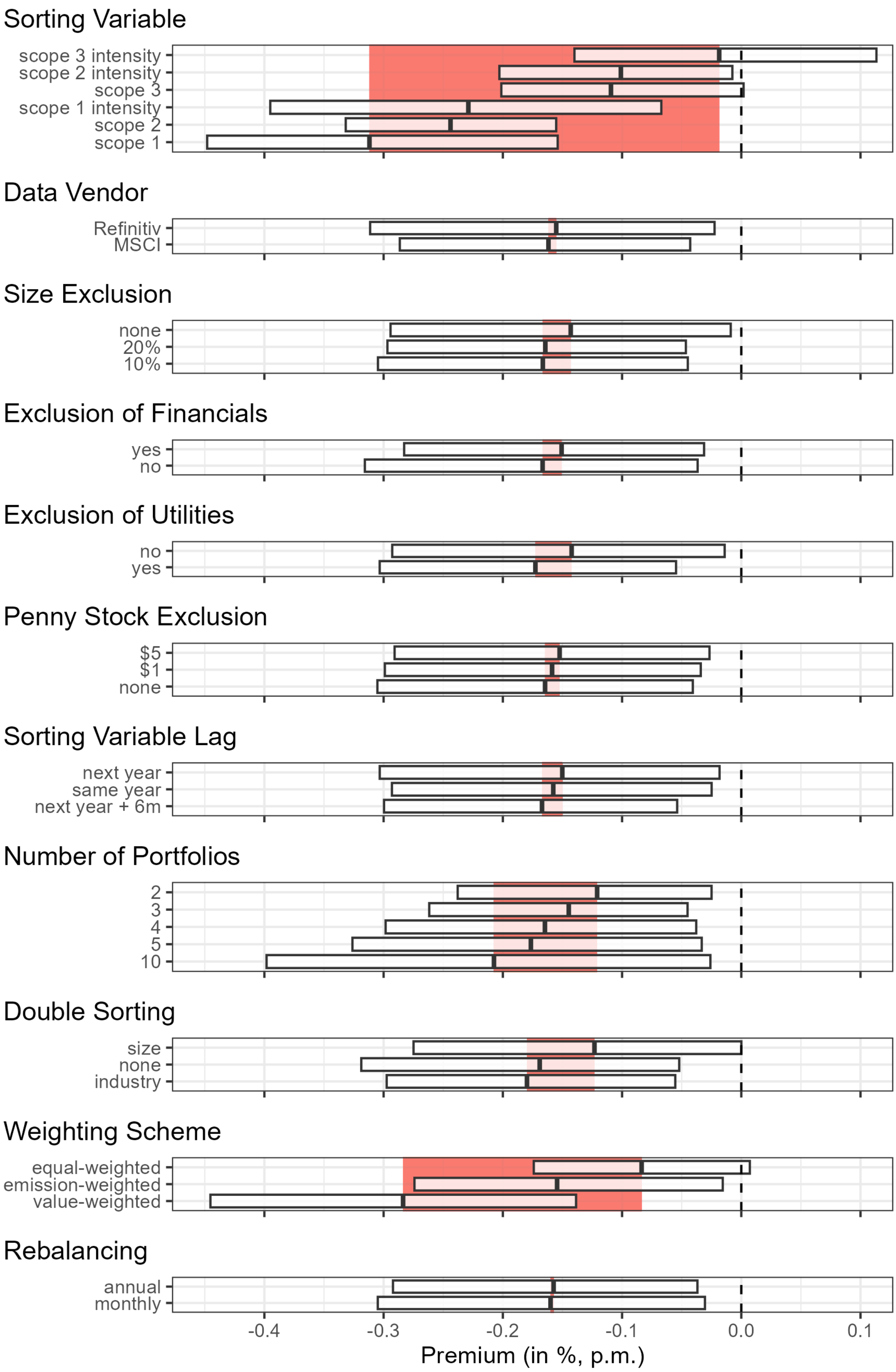
proxy they use to sort their portfolios. On the one hand, this is not very surprising, as there may well be economic rationale behind the choice of sorting variables and a risk premium is not expected for all scopes or intensities of carbon emissions. On the other hand, the size of the MAD is remarkable when considering that some studies derive their choice of sorting variables very similarly and yet come to different conclusions. For example, see Bolton and Kacperczyk (2024) and Aswani et al. (2024b) for a discussion of which variables are best suited to capture carbon (transition) risk. The forks weighting scheme, data vendor, size/industry adjustments via double sorts, number of portfolios, and sorting variable lag have the next biggest impact on non-standard errors in carbon premia. While these forks relate to the portfolio construction and premium calculation process, the forks concerning sample selection have only a minor influence.

Next, we examine how carbon premia vary when individual forks are held constant. Figure 4 shows boxplots of the distribution of carbon premia for each choice of a specific fork. From these boxplots, we can draw two conclusions. First, the width of the boxes, i.e., the interquartile range of carbon premia, gives an indication of the size of the non-standard errors. Second, the horizontal shift of boxes indicates that certain choices lead to systematically higher or lower carbon premia.

Most notably, the choice of the sorting variable affects the size of average carbon premium and non-standard errors, which was already pointed out earlier. The second largest impact on the distribution of carbon premia comes from the chosen weighting scheme. The boxplots indicate that, on average, equal- and emission-weighted portfolio sorts lead to higher carbon premia than value-weighted portfolio sorts. Moreover, the size of non-standard errors conditional on the weighting scheme suggests that equal-weighted portfolios that give relatively more weight to smaller stocks do lower the size

Figure 4: Impact of Fixing Specific Forks

This figure shows boxplots of the distribution of carbon premia when fixing a specific fork in BMG portfolio construction. The remaining 10 forks each vary in their choices as defined in Table 2.



of non-standard errors. The number of portfolios also has an influence on the size of the average carbon premium and non-standard errors. If researchers use median breakpoints to build BMG portfolios, the non-standard error is only about half the size compared to using decile portfolios. This seems intuitive, as decile portfolios contain fewer stocks for diversification and give relatively more weight to firms with extreme characteristics. Assuming monotonicity, the latter would also result in a more pronounced carbon premium. However, the higher the number of portfolios, the lower the carbon premium. The next biggest impact on average carbon premia and their variation comes from size/industry adjustments via double sorts and the chosen sorting variable lag. Despite the large time-series average MAD, the data vendor fork has only a minor influence on the distribution of average BMG returns. Fixing choices in the rebalancing, size and penny stock exclusion forks does not have material impact on the distribution of carbon premia. This seems plausible, as carbon emission data are usually updated annually and hardly any firm that reports carbon emission data falls below the size or price thresholds.

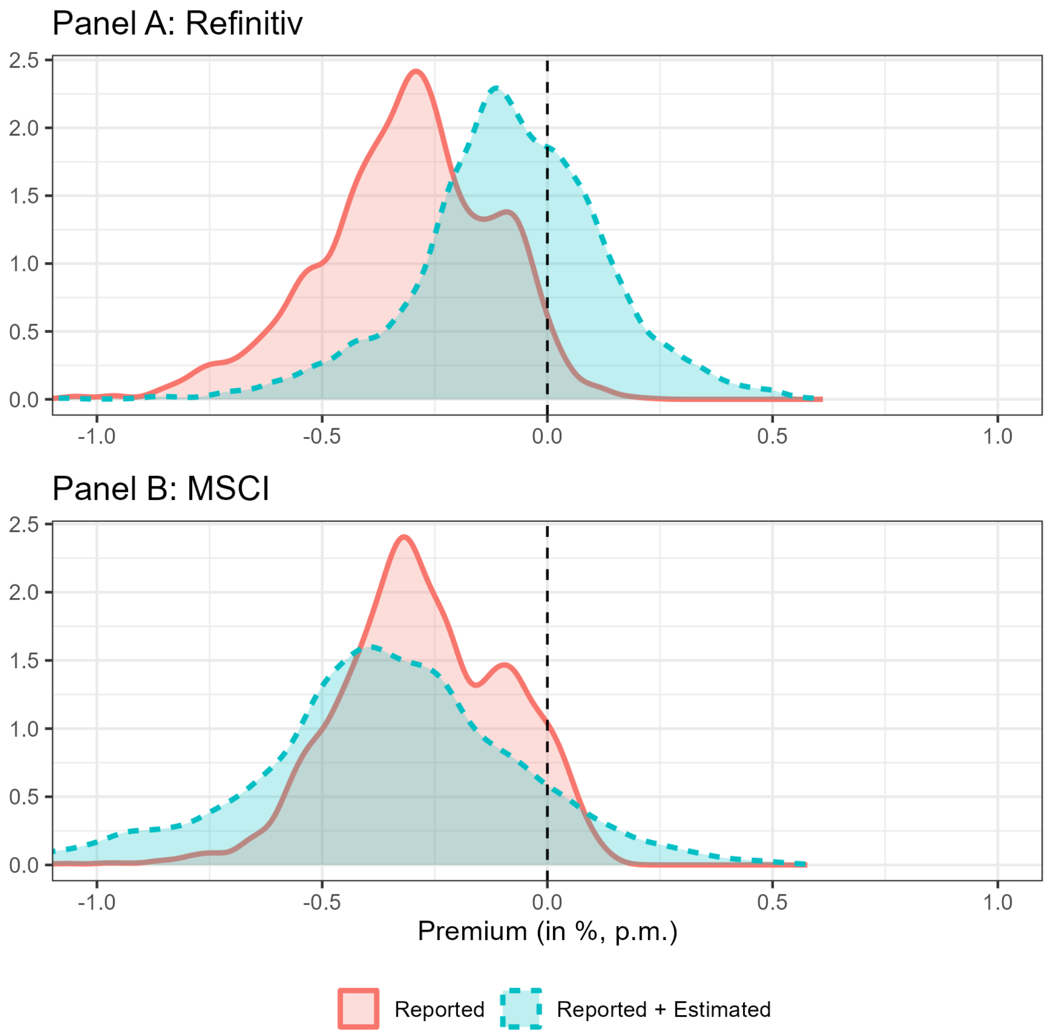
3.2 Impact of Estimated Carbon Emissions

The previous analyses relied on reported scope 1, scope 2, and scope 3 total emissions as well as emission intensities. Motivated by the insights of Aswani et al. (2024a, 2024b), this subsection further investigates the impact of sorting variables by examining reported versus estimated carbon emissions. While reported carbon emissions have reasonably high correlations across data vendors, estimated carbon emissions show much higher variation and are available for different samples of firms (Busch et al., 2022). Thus, we suggest that the inclusion of vendor estimated carbon emissions introduces a new source of non-standard errors in the carbon premium.

To investigate this possibility, we add another decision fork "include vendor estimates" to the BMG portfolio formation procedure described in section 2.2. As Refinitiv provides estimates only for a firm's combined scope 1+2 carbon emissions, we restrict the choice set in the sorting variable fork to scope 1+2 total emissions and scope 1+2 emission intensity. In Figure 5, we compare the resulting distributions of carbon premia derived from reported scope 1+2 total emissions (solid red line) to premia derived from reported+estimated scope 1+2 total emissions (dotted blue line). The inclusion of firms with estimated emissions more than doubles the sample size in most years. Also, we separately display the distributions of premia derived from Refinitiv emission data in Panel A and MSCI emission data in Panel B.

The two red lines in Panel A and B, representing the distributions of carbon premia derived from reported emissions of both data vendors, are very similar. This also mirrors the finding in Figure 4 that the data vendor has only a minor impact on average carbon premia derived from reported emission data. The distributions of carbon pre-

Figure 5: Distribution of Premia Derived from Estimated Carbon Data
This figure shows the distribution of carbon premia resulting from different methodological choices in portfolio construction. BMG portfolios are sorted on total scope 1+2 emission data provided by Refinitiv in **Panel A** and by MSCI in **Panel B**. The solid red (dashed blue) lines plot the distribution of carbon premia derived from reported (reported+estimated) carbon emission data.



mia derived from reported+estimated scope 1+2 total emissions show a different pattern. When including emissions estimated by Refinitiv, the distribution in Panel A shifts to the right. When including emission estimates from MSCI, the distribution shifts to the left. Replacing raw returns with factor-adjusted premia yields very similar results.

Numerically, this is presented in Table 5. Using Refinitiv data, the mean carbon premium derived from reported+estimated scope 1+2 total emission is 23 basis points larger. Using MSCI data, the mean carbon premium derived from reported+estimated scope 1+2 total emission is 9 basis points smaller. A similar pattern is observable, when considering emission intensities.

Table 5: Non-Standard Errors in Premia Derived from Estimated Carbon Data

This table reports means and non-standard errors (NSE) in carbon premia in % per month derived from reported versus reported+estimated carbon sorting variables. Results are based on carbon emission data from Refinitiv in **Panel A** and MSCI in **Panel B**. The last two columns contain the t-statistics of the Welch tests and the F-statistics of the Levene tests for comparing the mean and variance of the two distributions of carbon premia.

	Reported		Reported+Estimated		Difference	
Sorting Variable	Mean	NSE	Mean	NSE	Welch	Levene
Panel A: Refinitiv						
Scope 1+2	-0.31	0.25	-0.08	0.25	80.21	20.93
Scope 1+2 intensity	-0.29	0.33	-0.27	0.32	6.14	42.88
Panel B: MSCI						
Scope 1+2	-0.28	0.26	-0.37	0.34	-26.64	1238.26
Scope 1+2 intensity	-0.16	0.26	-0.27	0.35	-42.42	6.32

3.3 Alternative Carbon Sorting Variables

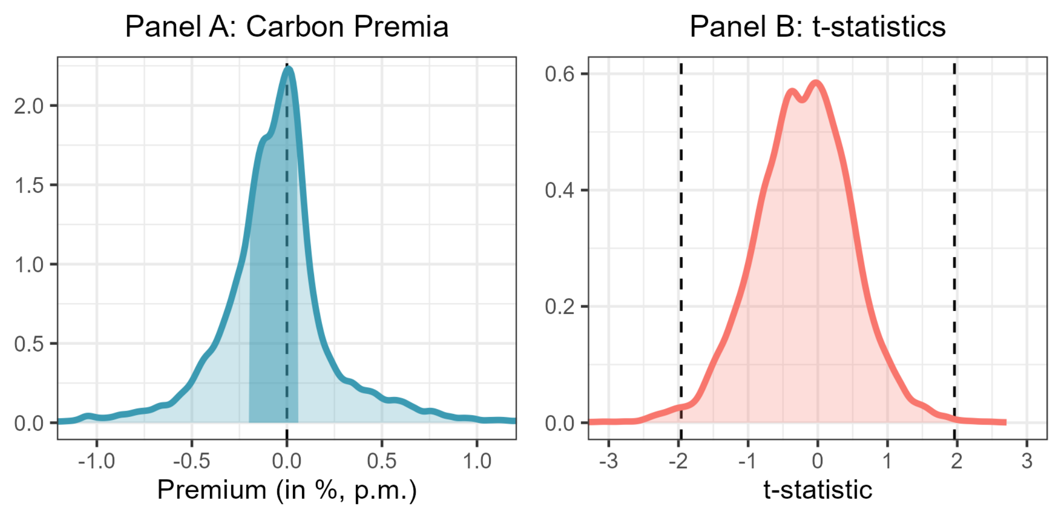
Carbon emissions are just a proxy for a firm's carbon transition risk and popular among researchers due to their easy accessibility and high availability. However, there are concerns that carbon emissions do not accurately capture carbon transition risk and other measures are being developed (e.g., Cenedese, Han, and Kacperczyk, 2024; Sautner et al., 2023a). This section therefore explores carbon premia derived from an alternative carbon risk sorting variable.

One approach is to identify firms' exposure to carbon transition risk through textual analysis of how companies disclose or communicate issues related to climate change (e.g., Li, Shan, Tang, and Yao, 2024; Sautner et al., 2023a). Sautner et al. (2023a) create a measure of firm-level climate change exposure based on textual analysis of earnings calls. This measure aims to capture the attention paid by earnings call participants to firms' climate change exposure by recording the proportion of the conversation that relates to the topic of climate change. Applying this measure to a sample of S&P 500 stocks, Sautner, van Lent, Vilkov, and Zhang (2023b) find a risk premium that is positive in some periods but often not statistically significant.

Methodologically, we replace the carbon emission sorting variables with the quarterly level of climate change exposure introduced by Sautner et al. (2023a). In addition to the overall climate change exposure measure $CC_{Exposure}$, which includes physical, regulatory, and business opportunity exposure, we also use the variant $CC^{Reg}_{Exposure}$, which focuses on regulatory aspects only. Additionally, we include the more narrowly defined climate change risk measures CC_{Risk} and CC^{Reg}_{Risk} in our set of possible sorting variables.

Due to the nature of the new sorting variables, we have to make a few changes in the portfolio construction compared to the previous methodology. First, we adjust the methodology to compute portfolio breakpoints. This becomes necessary as both versions of the exposure/risk measures show a value of zero across many firms and quarters. For the long portfolio, we define breakpoints from percentiles of non-zero sorting variable values. At each rebalancing date, the 50%, 25%, or 10% of firms with the highest climate change exposure/risk are assigned to the long portfolio. The short portfolio is kept constant and contains all firms whose sorting variable has a value of zero in the respective period. Second, we replace emission weights with climate change exposure/risk weights in the weighting scheme fork. Note that this weighting choice only applies to the long portfolio, as the short portfolio is equal-weighted due to overall exposure/risk values of zero. Third, we change the rebalancing dates from annually to quarterly, as earning calls are held on a quarterly basis. Fourth, we either merge sorting variables with returns in the same quarter or use the most recent one to three month lagged climate change exposure/risk data when calculating the carbon premium. Note that the first variant entails a possible look-ahead bias, while the second ensures availability of the climate change exposure/risk measures. As the measures can be calculated directly after an earnings call, there is no need to account for an additional reporting lag. The remaining forks defined in Table 2 are kept constant.

Figure 6: Distribution of Premia Derived from Climate Change Exposure
Panel A of this figure shows the distribution of carbon premia resulting from different methodological choices in portfolio construction. **Panel B** shows the distribution of the corresponding t-statistics. BMG portfolios are sorted on different variants of the Sautner et al. (2023a) firm-level climate change exposure/risk.



Panel A of Figure 6 shows the distribution of carbon premia across paths when using the climate change exposure/risk variables introduced by Sautner et al. (2023a) as sorting variables. The resulting distribution of carbon premia is similar to that obtained using sorting variables based on carbon emissions, centering around zero with tails on both sides. As shown in Table 6, the mean carbon premium is -0.06% per month. The 25th percentile return is -0.20% and the 75th percentile return is 0.06%, yielding an interquartile range of 0.26% per month, identical to the non-standard error derived from carbon emission sorting variables. The non-standard error is statistically significant, as column "Left-right" indicates. Panel B of Figure 6 indicates that most carbon premia are statistically indistinguishable from zero. Less than 1% of portfolio specifications yield a negative and statistically significant carbon premium, while approximately 1% of positive carbon premia are statistically significant. Basically, these findings mirror the results of Sautner et al. (2023a) that carbon emissions are positively correlated with their climate change exposure/risk variables.

Table 6: Non-Standard Errors in Premia Derived from Climate Change Exposure
This table reports summary statistics for BMG portfolio raw returns in % per month. BMG portfolios are sorted on Sautner et al. (2023a) firm-level climate change exposure/risk variables. Non-standard errors (*NSE*) are defined as the interquartile range of carbon premia resulting from different choices in portfolio construction described in Table 2. *Left-right* denotes the proportion of significant deviations to the left and right of the median carbon premia using a 5% significance level. Columns *Pos* and *Neg* indicate the proportion of positive and negative statistically significant carbon premia at the 5% level.

Mean	p25	p75	NSE	Left-right	Pos	Neg
-0.06	-0.20	0.06	0.26	(0.01, 0.00)	0.00	0.01

3.4 Time-Series Variation in Carbon Premia

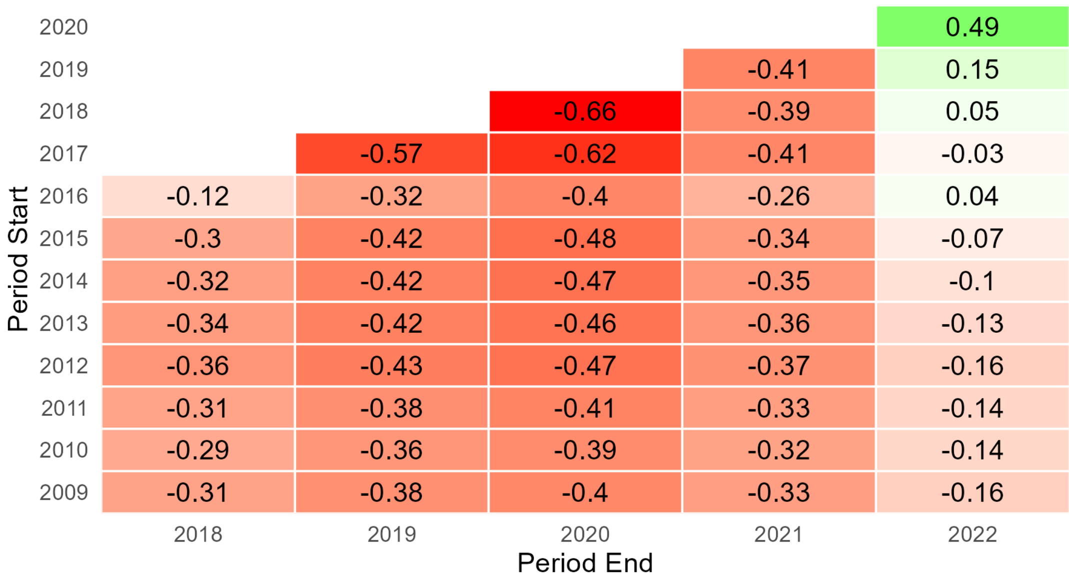
As already illustrated in Figure 2, there is strong time-series variation in carbon premia. The average BMG portfolio returns are mostly negative in the 2010s and positive in the last two years. The sample period chosen by researchers can therefore itself be considered as a source of non-standard errors.

Figure 7 shows average carbon premia in % per month when adding the sample period start and end as two additional forks in the BMG portfolio construction procedure.[8] While the average carbon premia are relatively stable over longer periods, the variation becomes larger when researchers only consider very short sample periods. For example, the two overlapping 3-year sample periods from January 2018 to December 2020 and January 2020 to December 2022 yield average carbon premia of -0.66% and 0.49% per month, respectively.

[8] For clarity, Figure 7 includes only period ends starting from 2018. Moreover, this selection aligns with the investigation periods of published studies examining the impact of carbon emissions on stock returns.

Figure 7: Sample Period as an Additional Fork

This figure shows the average carbon premia in % per month calculated over different sample periods between 2009 and 2022. The y-axis indicates the period start and the x-axis the period end. Results are reported for a minimum sample period of 3 years.



4 Economic Drivers of the Carbon Premium

In the search for economic drivers of the carbon premium, this study primarily builds on the theoretical model of Pástor et al. (2021). Their model assumes that unexpected shifts in climate concerns can lead to a short-term outperformance of green stocks, while brown stocks are expected to earn higher returns in equilibrium. First empirical evidence that tests this explanation for time-varying returns of green versus brown stocks is provided by Ardia et al. (2023) and Pástor et al. (2022). Ardia et al. (2023) use a sample of S&P 500 firms over the 2010 to 2018 period and quantify a firm's carbon transition risk by combined scope 1+2+3 carbon emission intensity. Pástor et al. (2022) analyze a larger sample of US stocks over the 2012 to 2020 period and use environmental scores from MSCI ESG ratings to quantify a firm's greenness.

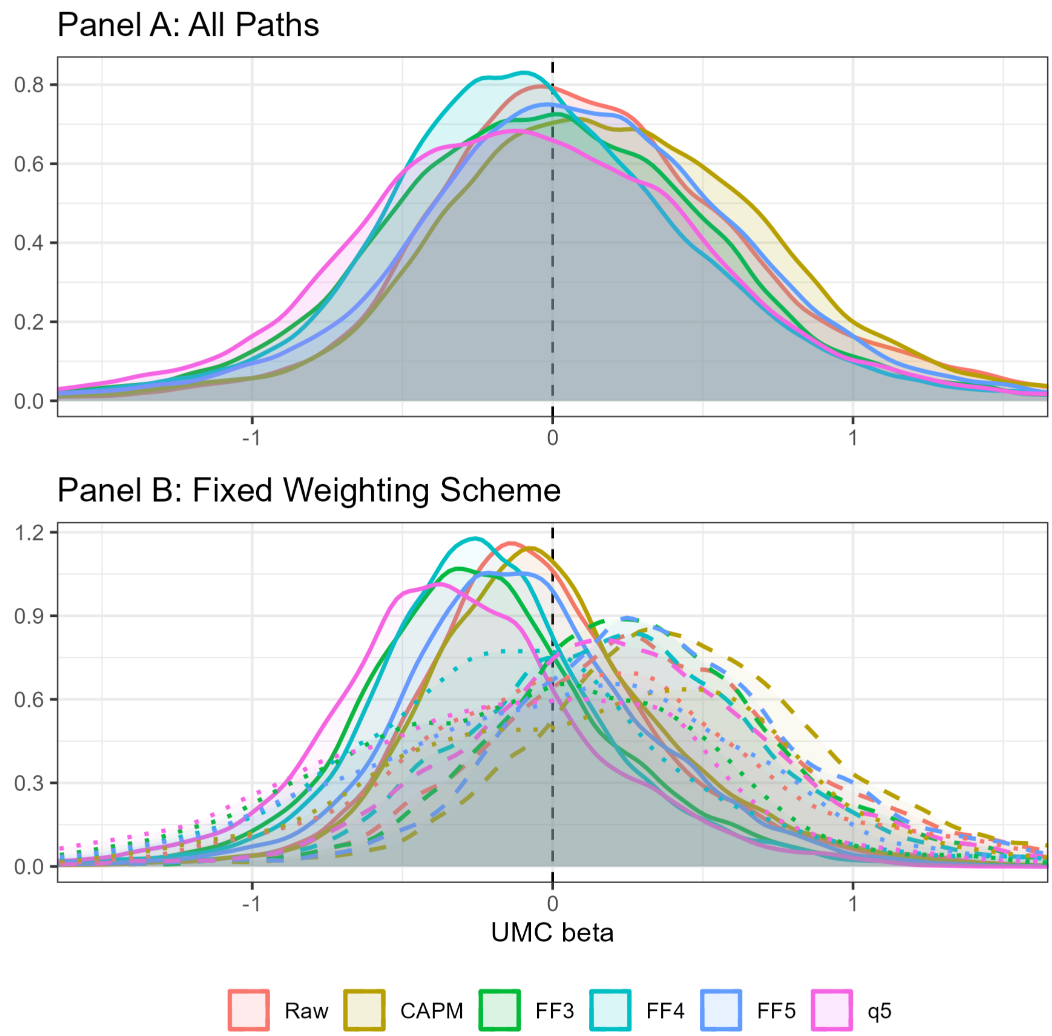
In contrast to these two studies, which rely on quite specific methodological choices, this research aims to provide a broader view on the time-series dependence of green stock returns and climate media attention. Specifically, this research examines (1) if the time-series of BMG returns is related to unexpected shifts in climate concerns and (2) if controlling for such shifts mitigates non-standard errors in carbon premia. To measure climate concerns, we rely on the MCCC index introduced by Ardia et al. (2023). For each of the 116,640 portfolio construction paths, we separately regress the time-series of BMG portfolio returns against monthly unexpected changes in MCCC:

$$r_t = \alpha + \beta^{UMC} UMC_t + \epsilon_t, \quad (4)$$

where r_t is the monthly return of a BMG portfolio, UMC_t is the unexpected change in media climate concerns from month $t-1$ to t, and ϵ_t is the measurement error. Following Pástor et al. (2022), UMC_t is calculated as the prediction error from a 36-months rolling AR(1) model.

Figure 8: Media Climate Concerns and Carbon Premia

This figure shows the distribution of β^{UMC} coefficients across paths from equation (4). The dependent variables are either raw BMG returns or factor-adjusted premia as denoted by the different colors of the distribution plots. The explanatory variable UMC_t is the monthly unexpected change in media climate change concerns as introduced by Ardia et al. (2023). **Panel A** includes β^{UMC} coefficients across all 116,640 paths and **Panel B** shows distinct coefficient distributions conditional on the fork "weighting scheme". The solid, dashed, and dotted curves indicate equal-, value-, and emission-weighted portfolio specifications, respectively.



The distribution of β^{UMC} coefficients across paths is plotted in Figure 8. This figure also includes distributions of beta coefficients from regression variants when unadjusted raw returns as the dependent variable in equation (4) are replaced by the unexplained part of factor-adjusted BMG premia, i.e., the sum of the alpha coefficients and residuals. Panel A plots the distribution of β^{UMC} coefficients across all 116,640 paths. Although the median beta coefficients for raw BMG returns and factor-adjusted premia are slightly negative, the majority of values are centered around zero. At first glance, one might conclude that unexpected changes in MCCC do not significantly add to the explanation of time-series variation in carbon premia. This contradicts the findings of Ardia et al. (2023) and Pástor et al. (2022). On closer inspection, however, the beta coefficients differ greatly depending on which portfolio construction path was taken. In a similar approach as used in section 3.1 to identify which forks induce the largest variation in carbon premia, we continue to investigate which methodological choices lead to carbon premia that vary with unexpected changes in climate concerns. While most methodological decisions have a negligible effect, one fork stands out. When fixing the weighting scheme to consider only equal- and emission-weighted portfolio sorts, about 70% of the beta coefficients on q5-adjusted premia become negative, of which 11% are statistically significant at the 5% level. A similar pattern is found for regressions on BMG raw returns and other factor-adjusted premia as illustrated in Panel B of Figure 8.

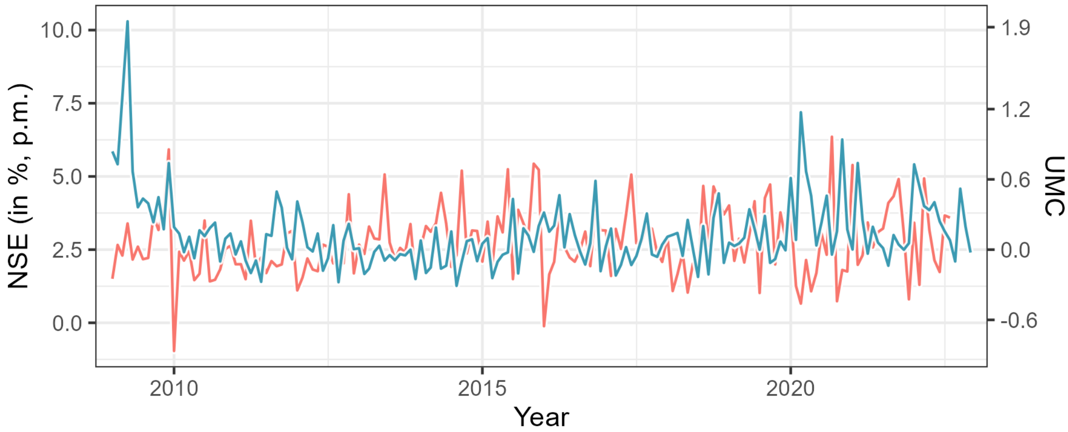
Why does the weighting scheme have such a significant impact? First, and most obviously, equal-weighted portfolios give more weight to smaller firms than value weighted portfolios. When climate concerns rise unexpectedly, certain investors may reallocate their funds from brown to green stocks. It's hard to argue that stocks with higher market capitalization should be more susceptible to this investment behavior and experience larger repricing effects than firms with smaller market capitalization. Second, if investors build portfolios according to their environmental (risk) preferences, they are unlikely to hold value-weighted portfolios. Instead, they aim to deviate from the market portfolio and overweight stocks based on their greenness. Third, when considering unscaled total emissions, larger firms are more likely to be categorized into the brown (long) portfolio by construction. If a large firm nevertheless ends up in the green (short) portfolio, its high weighting can distort the return estimates of the entire portfolio.

Mostly negative β^{UMC} coefficients indicate that carbon premia are negatively related to innovations in MCCC, which largely confirms the mechanism proposed by Pástor et al. (2021, 2022), even if it does not hold for all specifications. Unexpected changes in climate concerns may therefore partly explain the absence of a consistently positive carbon premium. Additionally, the large variation in β^{UMC} carbon premia across paths indicates that not just the carbon premium varies with unexpected shifts in climate concerns but also the strength and direction of this time-series relation itself varies across paths.

Further insight into the effect of climate media attention on carbon premia can be gained by looking at non-standard errors in carbon premia over time, which are plotted in blue in Figure 9. Since non-standard errors are not constant over time, they could capture uncertainty in carbon premia that researchers may want to control for. Such uncertainty could be caused by return patterns that affect BMG returns but have a different source than the proposed sorting variable.

Figure 9: Time-Series of Non-Standard Errors in Carbon Premia

This figure plots the non-standard errors (NSE) in carbon premia over the 2009 to 2022 period in blue. The monthly unexpected changes in media climate change concerns (UMC) are plotted in red.



To test this possibility, we examine whether the time-series of non-standard errors in carbon premia is related to unexpected shifts in climate concerns. UMC_t is a suitable candidate state variable to control for, because it is likely to affect carbon premia as shown above, but theoretically stems from other sources than a premium motivated by a carbon transition risk. Specifically, we regress the time-series of non-standard errors in carbon premia against unexpected changes in climate concerns:

$$NSE_t = \alpha + \gamma^{UMC} UMC_t + \gamma^{\sigma} \sigma_t^{ret} + \epsilon_t, \tag{5}$$

where NSE_t is the monthly non-standard error in carbon premia across paths, UMC_t is the unexpected change in MCCC from month $t-1$ to t, σ_t^{ret} is the standard deviation in returns of all US common stocks listed at the NYSE, NYSE American (formerly AMEX), or NASDAQ in month t, and ϵ_t is the measurement error.

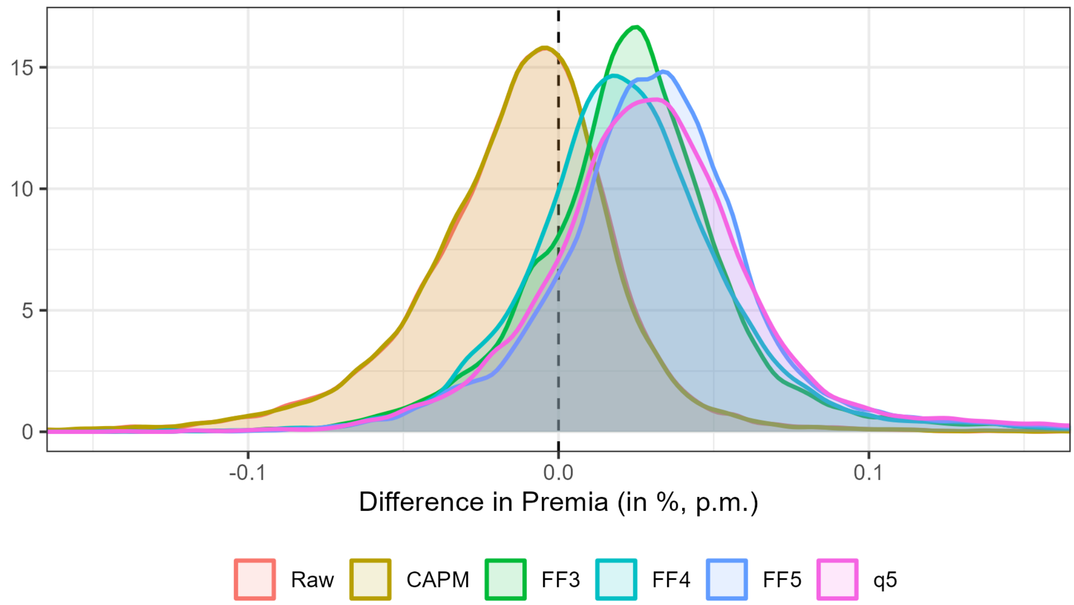
Table 7: Non-Standard Errors in Carbon Premia and Media Climate Concerns

This table reports time-series regression results. The dependent variable NSE_t is the monthly non-standard error in carbon premia across BMG portfolio construction paths. UMC_t is the unexpected change in media climate concerns from month $t-1$ to t and $Volatility_t$ is the time-series of the cross-sectional standard deviation in US stock returns. Newey and West (1987) standard-errors are given in parentheses. Significance levels: *p<0.1, **p<0.05, ***p<0.01.

	NSE					
	Raw	CAPM	FF3	FF4	FF5	q5
UMC	-0.5973*	-0.4588*	-0.4828**	-0.5223**	-0.3927*	-0.3191
	(0.3074)	(0.2772)	(0.2272)	(0.2253)	(0.2246)	(0.2342)
Volatility	0.1007***	0.0810**	0.0808**	0.0672***	0.0773**	0.0732***
	(0.0358)	(0.0323)	(0.0357)	(0.0251)	(0.0348)	(0.0259)
Observations	164	164	164	164	164	164
Adjusted R^2	0.2524	0.2098	0.2478	0.2304	0.2348	0.2504

As shown in Table 7, unexpected changes in climate concerns are negatively related to the size of non-standard errors in carbon premia. In the first column the dependent variable is the non-standard error in raw BMG portfolio returns. In the remaining five columns, the dependent variable is the non-standard error in the unexplained part of factor-adjusted premia. We follow Walter et al. (2024) by controlling for stock market volatility, as in times of high market volatility, it is intuitive to assume that carbon premia are confounded by this cross-sectional dispersion. Indeed, controlling for stock market volatility significantly increases the adjusted R^2. More importantly, however, the γ^{UMC} coefficients remain negative and statistically significant across most specifications. In other words, non-standard errors are lower when climate concerns increase unexpectedly. Compared with the previous finding that carbon premia are mostly negatively correlated with UMC_t, this suggests phases of repricing when climate concerns rise unexpectedly. Such phases are characterized by low methodological uncertainty, as the carbon premia are robustly negative across a large number of paths.

Figure 10: Differences in Carbon Premia Through Media Climate Concerns
This figure shows the distribution of differences between the carbon premia as plotted in Figure 1 and the counterfactual carbon premia adjusted for unexpected shifts in climate concerns.



Lastly, we investigate how controlling for UMC_t-exposure affects the distribution of carbon premia. Therefore, we calculate counterfactual carbon premia by eliminating the effect of unanticipated repricing phases due to shocks in climate concerns, as calculated in equation (4). Differences in raw and factor-adjusted premia across portfolio construction paths are plotted in Figure 10. As expected, the distribution of the counterfactual carbon premia shifts to the right compared to the distribution of the premia plotted in Figure 1. Interestingly, the differences for raw and CAPM premia are centered around zero. For the remaining factor-adjusted premia, however, the counterfactual premia are significantly higher than the UMC_t-unadjusted premia. For the FF5- and q5-adjusted premia, this difference amounts to an average of 3.2 basis points per month or 0.4% per year. In summary, controlling for climate concerns-induced phases of negative BMG returns can partially help explain the lack of a consistently positive carbon premium.

5 Conclusion

Methodological uncertainty, i.e., non-standard errors, has a substantial impact on the carbon premium and amount to 0.26% per month. The largest impact on non-standard errors comes from the selected sorting variable including estimated carbon emissions, the weighting-scheme, size/industry adjustments, and the sample period. However, the majority of 100,000 methodological paths generates carbon premia that are indistinguishable from zero with a mean of -0.16% per month. Thus, the distribution of possible carbon premia does currently not mirror the conjecture of theoretical models that, in equilibrium, brown stocks have higher expected returns than green stocks.

Unexpected shifts in climate concerns offer an explanation for this discrepancy. When climate concerns rise unexpectedly, carbon premia often become more negative due to repricing effects. These "climate shocks", as described by Pástor et al. (2021), can help explain the lack of a consistently positive carbon premium anticipated by theory. Additionally, these climate shocks are negatively correlated with non-standard errors, indicating reduced methodological uncertainty during periods of heightened climate concerns. We conclude that it is crucial to address non-standard errors and to control for unexpected shifts in climate concerns in carbon premium research.

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