Measuring and Optimizing the Risk and Reward of Green Portfolios

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KEY FINDINGS

- We study the performance of green portfolios constructed using a broad range of climate-related environmental metrics. A comparison between popular portfolio construction methodologies shows that Treynor–Black weights offer the most robust performance.
- Green portfolios (e.g., low-carbon portfolios) realize positive alphas in excess of Fama–French factors in the United States, but a significant portion of that alpha is explained by an unexpected increase in climate concerns over the past decade, rather than positive expected returns.
- Investors over the past seven years have borne a cost for holding green assets instead of brown assets in China, implying a positive carbon premium. The US experience may offer hints for the future of green investing in China and other developing economies.

ABSTRACT

We study the performance of green portfolios in both the US and Chinese markets, constructed using a broad range of climate-related environmental metrics, including carbon emissions, water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource use. We compare several popular long-only and long–short green portfolio construction methodologies and find that a method based on Treynor–Black weights offers the most robust performance, thanks to its ability to quantify alphas for individual assets using only a small number of parameters. In the United States, green portfolios (e.g., low-carbon portfolios) have realized positive alphas in excess of Fama–French factors, a significant portion of which can be explained by an unexpected increase in climate concerns over the past decade, rather than positive expected returns. In contrast, Chinese investors have borne a cost for holding green assets instead of brown assets over the past seven years, implying a positive carbon premium, the opposite of US markets.

There is an increasing awareness of the urgency required to combat climate change and environmental pollution from central governments, financial regulators, and investors around the world. As of August 2022, more than 130 countries have committed to carbon-neutrality targets in various forms, representing approximately 80% of the world population and 90% of the world's GDP, according to a tracker co-led by the organization Oxford Net Zero.[1] This shift in public attention is particularly

[1] See

relevant to financial markets for two reasons. First, investors need to understand whether firms with lower emissions and levels of environmental pollution lead to better or worse returns for their portfolios and how to construct green portfolios with the best risk-adjusted returns (Krueger, Sautner, and Starks 2020). Second, by better understanding the financial performance of green portfolios, regulators and other stakeholders will be able to improve their insights into the transitional risk to the market, which will enable them to design policies and strategies to help allocate resources for carbon-neutral goals.

In this article, we systematically quantify the investment performance of green portfolios constructed using a wide range of environmental measures, with a specific focus on carbon emission variables, but also including environmentally relevant variables such as water consumption and waste disposal, among others. We compare several popular long-only and long–short green portfolio construction methodologies and study both the US and Chinese markets—the two countries with the highest total carbon emissions. The United States is a developed market that started its focus on environmentally aware investing in the early 2010s, in sharp contrast to the developing Chinese market, which started later but in recent years has rapidly begun to catch up.

Our environmental data come from S&P's Trucost Environmental dataset. It provides a wide range of environmental measures for global companies that are updated annually from 2005–2020, including carbon emissions, water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource use. We combine this dataset with stock returns and factor data for the US and Chinese stock markets. Our final dataset contains 3,969 US companies and 2,088 Chinese companies.

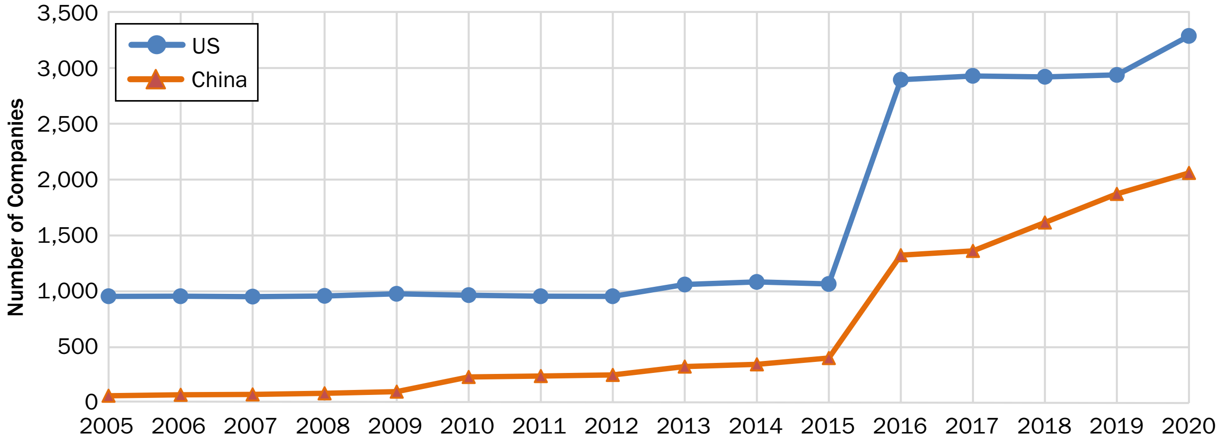
The aggregate levels of carbon emission, water consumption, and waste disposal in our data decrease over time, although the firm-level growth rates in these measures show a high degree of heterogeneity. While the aggregate levels of these measures for Chinese companies are generally larger than those for US companies, the rates of decrease are also generally larger for Chinese companies. In addition, different enve oa -.2 (e c)Span <5.7 (.m)0.6 (e)4.2 (n)17.6 (ho)3 (a)0.80.6 (v)o.6 rorvs 31.6 (v

We study the source of greeniums for the US market. Fama–French five-factor

Our empirical findings are generally consistent with this literature, but may appear at odds with the findings of Bolton and Kacperczyk (2021a, 2022) in the

EXHIBIT 1

The Number of US and Chinese Companies Covered by the Trucost Environmental Data Each Year



emissions according to the Greenhouse Gas Protocol—Scope 1, 2, and 3.[6] Both (3) and (4) are classified into direct and indirect emissions. Nearly 100% company-years in our sample have valid values for all of these measures.[7]

The Trucost Environmental data also include measures for water consumption and waste disposal. Like carbon emissions, both the water consumption and waste disposal data consist of four types: (1) the total level (in cubic meters or tons), (2) the intensity, (3) the monetary value, and (4) the impact ratio. They are further classified into several subcategories. However, the coverage of these measures is not as complete as for carbon emissions, and we consider only those measures with at least 75% valid company-year values. For water consumption, we have (1), (2), (3), and (4) for the total volume of water directly abstracted and purchased. For waste disposal, we have (1) and (2), which are further classified into measures of direct landfilled waste and direct incinerated waste, and (3) and (4), which are further classified into measures of directly produced and indirectly produced waste.

In addition to carbon emissions, water, and waste, the Trucost Environmental data also include the monetary value and impact ratio for several other measures, including land and water pollutants (in total only), air pollutants (both direct and indirect), and natural resource use (in total only). All of these measures have coverage greater than 75% and are therefore included in our analysis.

In addition to the four environmental measures included in the original data, we also investigate the impact of their growth rate (5), that is, the annual percentage change of the total level for each measure. To mitigate the impact of outliers, we follow Bolton and Kacperczyk (2021a) to winsorize measures (2)–(5) at the 2.5% level and take the natural logarithm of (1) and (3) to obtain log-level measures.

[6] Scope 1 emissions cover greenhouse gas emissions from operations that are owned or controlled by the company. Scope 2 emissions cover emissions from the consumption of purchased electricity, heat, or steam by the company. Scope 3 emissions cover other indirect emissions not covered in Scope 2, such as from the extraction and production of purchased materials and fuels, transport-related activities in vehicles not owned or controlled by the reporting entity, electricity-related activities, outsourced activities, waste disposal, and so on. See https://ghgprotocol.org/corporate-standard. The dataset also provides measures for direct emissions (which equals Scope 1 emissions plus those of three additional greenhouse gases) and emissions from direct suppliers. We do not study them separately because these measures are numerically close to Scope 1 and 2 emissions, respectively.

[7] We treat both null and zero values in the data as invalid values.

Returns and Factors

We obtain monthly dividend-adjusted return data for both US and Chinese companies from 2006–2021. The US data come from the CRSP dataset,[8] which covers monthly returns for US stocks listed on the NYSE, AMEX, and NASDAQ. The Chinese data come from the Wind database,[9] which provides monthly returns for stocks listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange.

We obtain monthly Fama–French five-factor (Fama and French 2015) data for both the US and Chinese markets. The US data are obtained from Kenneth R. French's website,[10] and the Chinese data are obtained from a database maintained by the China Asset Management Academy of the Central University of Finance and Economics.[11] Both data include the time series of the market factor, the size factor (small minus big, i.e., SMB), the value factor (high minus low, i.e., HML), the profitability factor (robust minus weak, i.e., RMW), and the investment factor (conservative minus aggressive, i.e., CMA). The risk-free rate is also provided.[12]

To investigate the source of returns from our green portfolios, we also use the MCCC index developed by Ardia et al. (2022) as a proxy for climate risk concerns in the market.[13] This index is constructed based on data from 10 major US newspapers and two major newswires for the period January 2003–June 2018. It captures the number and negativity of climate news stories and focuses on risk.

ANALYSIS OF ENVIRONMENTAL MEASURES

The comprehensiveness of the Trucost Environmental dataset warrants a detailed exposition of the data's statistical properties. In this section, we present the summary statistics, the time-series characteristics, and the correlations between the various measures of the Trucost Environmental data.

Summary Statistics

Exhibit 2 presents the summary statistics of carbon emission measures for all US and Chinese companies from 2005–2020, where each sample corresponds to a company-year. In our sample, Chinese companies have higher average carbon emissions compared to US companies, reflecting the fact that the Trucost Environmental dataset covers more medium- and small-cap companies in the US than in China. In addition, the average growth rates for Scope 1, Scope 2, and Scope 3 carbon emissions of Chinese companies are 12.67%, 15.33%, and 10.70%, respectively, compared to 7.69%, 10.04%, and 6.62%, respectively, for US companies. This is consistent with the fact that companies in developing countries generally have faster growth in carbon emissions.

Exhibit 3 presents the summary statistics of measures for water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource uses for all US and Chinese companies from 2005–2020. On average, Chinese companies in our sample have greater water consumption, larger amounts of waste disposal

[8] We obtain the CRSP data from the Wharton Research Data Service.

[9] See https://www.wind.com.cn/en/default.html.

[10] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[11] These factors use the same methodology as Fama and French (2015) but are based on Chinese data. See http://sf.cufe.edu.cn/kydt/kyjg/zgzcglyjzx/xzzq.htm.

[12] As a robustness check, we additionally include the momentum factor (Carhart 1997) and consider a six-factor model in Appendix I.3 of the online appendix.

[13] The data can be downloaded from https://sentometrics-research.com.

EXHIBIT 2

Summary Statistics of Carbon Emission Measures (2005–2020)

	Mean	Std	Min	25%	50%	75%	Max
Panel A: US Companies							
Log Total Level							
Scope 1	9.92	3.09	–4.61	7.91	9.91	11.80	18.87
Scope 2	10.05	2.54	–1.95	8.60	10.28	11.74	17.17
Scope 3	11.77	2.47	–1.21	10.15	11.97	13.50	19.18
Intensity							
Scope 1	139.67	434.12	0.47	4.16	13.91	31.54	2,393.66
Scope 2	31.07	37.07	1.02	8.07	17.53	41.59	179.63
Scope 3	139.50	136.43	22.42	37.83	87.53	189.99	577.86
Growth Rate							
Scope 1	7.69%	35.57%	–62.28%	–7.57%	2.71%	15.19%	145.98%
Scope 2	10.04%	38.72%	–54.52%	–7.37%	2.88%	17.09%	170.84%
Scope 3	6.62%	24.55%	–43.87%	–5.60%	3.45%	14.39%	91.89%
Log Monetary Value							
Direct	–0.24	2.94	–6.00	–2.25	–0.28	1.60	6.40
Indirect	1.85	2.26	–3.13	0.31	2.03	3.51	6.00
Impact Ratio							
Direct	0.53	1.64	0.00	0.02	0.05	0.12	8.92
Indirect	0.64	0.59	0.09	0.22	0.43	0.88	2.58
Panel B: Chinese Companies							
Log Total Level							
Scope 1	10.55	2.80	0.41	8.74	10.15	12.00	20.19
Scope 2	10.11	1.92	0.60	8.83	10.00	11.30	18.86
Scope 3	11.93	1.89	2.50	10.64	11.85	13.20	18.61
Intensity							
Scope 1	407.85	1,213.13	0.54	12.24	24.07	92.53	6,459.23
Scope 2	41.98	53.67	1.07	11.82	22.07	48.87	246.31
Scope 3	203.06	179.56	24.81	66.48	153.84	283.19	798.48
Growth Rate							
Scope 1	12.67%	42.72%	–67.35%	–7.96%	6.77%	24.01%	176.31%
Scope 2	15.33%	44.84%	–55.92%	–8.30%	7.47%	26.91%	198.51%
Scope 3	10.70%	31.20%	–52.00%	–6.87%	7.31%	23.58%	109.41%
Log Monetary Value							
Direct	0.37	2.67	–4.35	–1.43	–0.03	1.83	6.90
Indirect	2.00	1.74	–1.37	0.73	1.91	3.23	5.76
Impact Ratio							
Direct	1.54	4.59	0.00	0.05	0.09	0.35	24.50
Indirect	0.95	0.80	0.10	0.36	0.72	1.34	3.42

(both landfill and incineration), more land and water pollutants, more air pollutants, and greater natural resource use than US companies.

Time-Series Trends

Here we examine the change of these environmental measures over time. For each year, we calculate the cross-sectional average of each carbon emission measure. Exhibit 4 shows the time series of these averages for both US and Chinese companies.

EXHIBIT 3 *(con in ed)*

Summary Statistics for Measures of Water Consumption, Waste Disposal, Land and Water Polluants, Air Pollutants, and Natural Resource Use (2005–2020)

	Mean	Std	Min	25%	50%	75%	Max
Land and Water Pollutants							
Log Monetary Value	0.15	1.92	–3.54	–1.24	0.07	1.42	4.39
Impact Ratio	0.26	0.49	0.01	0.04	0.09	0.22	2.59
Air Pollutants							
Log Monetary Value-Direct	–0.80	2.85	–5.98	–2.79	–1.14	1.08	5.59
Log Monetary Value-Indirect	1.11	1.71	–2.23	–0.13	1.06	2.32	4.71
Impact Ratio-Direct	0.50	1.36	0.00	0.01	0.03	0.16	7.15
Impact Ratio-Indirect	0.40	0.36	0.04	0.15	0.29	0.50	1.56
Natural Resource Use							
Log Monetary Value	–0.30	2.15	–3.91	–1.80	–0.59	0.84	5.52
Impact Ratio	0.35	1.24	0.01	0.03	0.05	0.11	7.05

Like the observations documented by Bolton and Kacperczyk (2021a), the level of carbon emissions, its intensity, monetary value, and impact ratio for US companies generally decline over time, likely as a result of improvements in energy efficiency, technological innovation, or an increase in the reliance on renewable energy sources. In addition, we find that a decline in carbon emissions holds not only for the United States but also for China.

We observe that the recent decrease in direct carbon emissions is faster than that found in indirect carbon emissions. For the overall carbon emission level and its intensity, the decrease is faster in Scope 1 emissions than in Scope 2 or Scope 3 emissions. For the monetary value and impact ratio, the decrease is faster for direct emissions than indirect emissions, especially in China. The sharp decline in most measures from 2015–2016 is likely due to the increased coverage of the Trucost Environmental data, which added small- and mid-cap companies in 2016, as shown in Exhibit 1.

Although most average carbon emission measures decrease in our sample period, the averages of cross-sectional annual growth rates of carbon emissions are generally positive (see Exhibits 4e and 4f). This result implies that, for both the US and China, the overall decline of carbon emissions is faster for larger companies with higher levels of carbon emissions, while smaller companies are still increasing their carbon emissions, on average.

In addition, Exhibit 5 shows the time series of the annual cross-sectional average for water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource use. Like carbon emissions, most of these environmental measures have decreased in recent years. In addition, Chinese companies show a more rapid decline than US companies in our sample.

Correlation between Environmental Measures

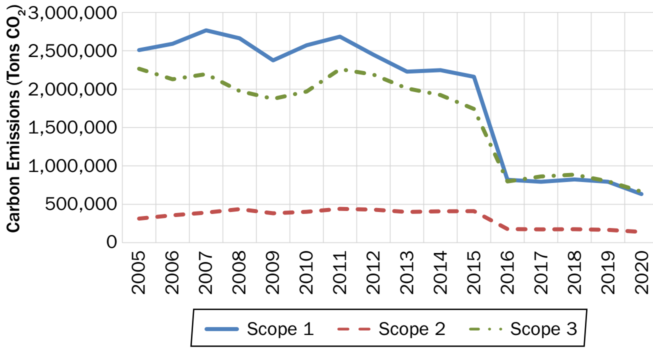
In the previous section, we uncovered a number of similarities between patterns in the levels of several environmental measures, leading us to examine the correlation between these measures.

Exhibits 6 and 7 show the correlation matrix between all environmental measures in our analysis for US and Chinese companies, respectively. We first calculate the cross-sectional correlations between different measures for each year and then take the average of the annual correlation matrices from 2005–2020. In both

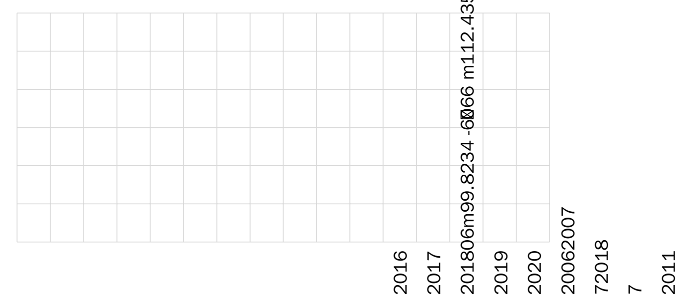
EXHIBIT 4

Time Series of Annual Cross-Sectional Average Carbon Emission Measures

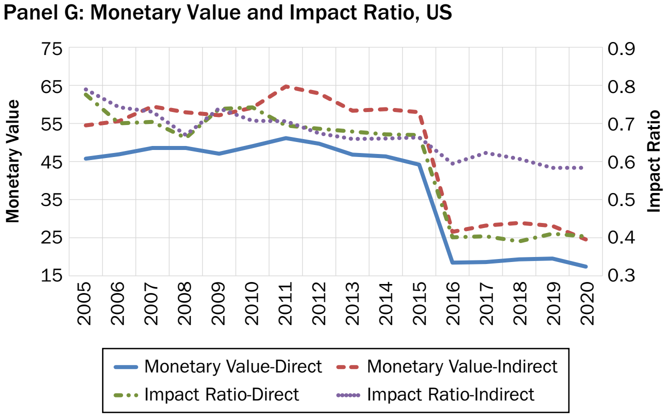
Panel A: Carbon Emissions, US



Panel B: Carbon Emissions, China



Panel G: Monetary Value and Impact Ratio, US



Panel H: Monetary Value and Impact Ratio, China

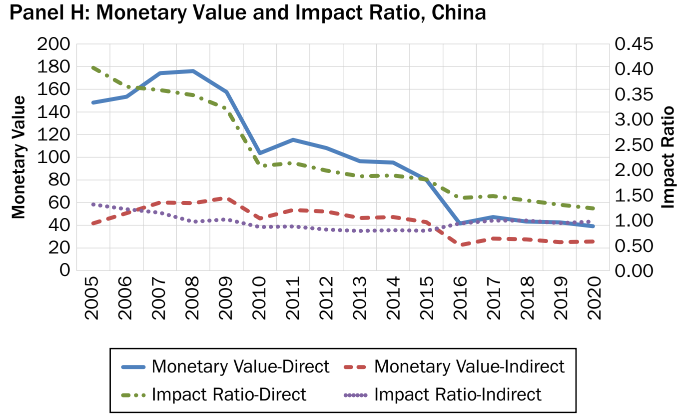
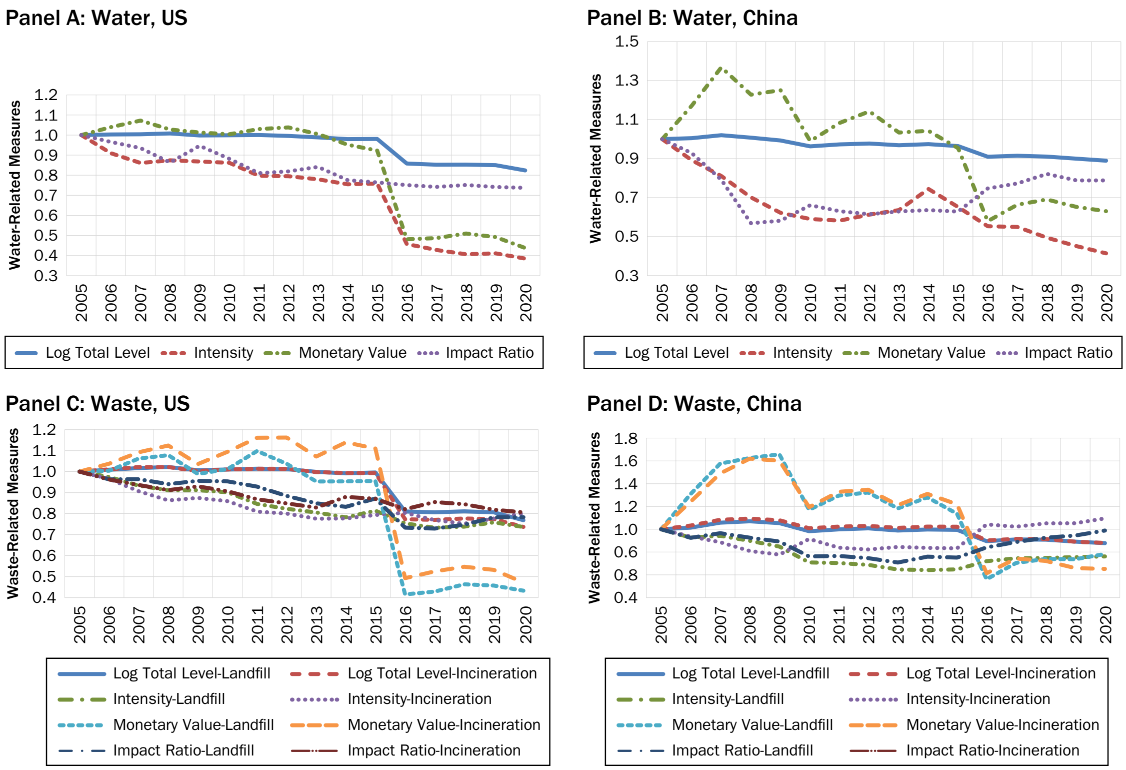


EXHIBIT 5

Time Series of Annual Cross-Sectional Average Water Consumption, Waste Disposal, Land and Water Pollutants, Air Pollutants, and Natural Resource Use



NOTE: All time series for water and waste are standardized to start with a value of 1.0 in 2005 to help with visualization.

EXHIBIT 6

Correlation Matrix of Environmental Measures: US

			Carbon												Water					Waste										Land & Water Pollutants		Air Pollutants				Natural Resource Use	
			Log Total Value			Intensity			Growth Rate			Log Monetary		Impact Ratio							Log Total Value		Intensity		Growth Rate		Log Monetary		Impact Ratio				Log Monetary		Impact Ratio			
			Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3	Scope 1	Scope 2	Scope 3	Direct	Indirect	Direct	Indirect	Log Total Value	Intensity	Growth Rate	Log Monetary	Impact Ratio	Landfill	Incineration	Landfill	Incineration	Landfill	Incineration	Landfill	Incineration	Landfill	Incineration	Log Monetary	Impact Ratio	Direct	Indirect	Direct	Indirect	Log Monetary	Impact Ratio
Carbon	Log Total Value	Scope 1	1.0	0.7	0.8	0.6	0.4	0.5	(0.0)	(0.0)	(0.1)	1.0	0.8	0.6	0.6	0.8	0.4	(0.0)	0.8	0.4	0.7	0.7	0.4	0.2	(0.0)	(0.0)	0.8	0.7	0.5	0.4	0.8	0.4	0.9	0.8	0.5	0.5	0.8	0.5
		Scope 2	0.7	1.0	0.8	0.1	0.5	0.3	(0.0)	0.0	(0.1)	0.7	0.9	0.1	0.4	0.7	(0.0)	(0.0)	0.8	0.2	0.8	0.8	0.3	0.2	(0.0)	(0.0)	0.8	0.9	0.2	0.4	0.8	0.2	0.7	0.9	0.1	0.4	0.8	0.2
		Scope 3	0.8	0.8	1.0	0.2	0.2	0.6	(0.0)	(0.0)	(0.1)	0.8	1.0	0.2	0.5	0.7	0.2	(0.1)	0.9	0.3	0.8	0.8	0.3	0.1	(0.1)	(0.0)	0.8	1.0	0.3	0.5	0.9	0.3	0.8	1.0	0.2	0.5	0.9	0.3
	Intensity	Scope 1	0.6	0.1	0.2	1.0	0.2	0.4	0.0	0.0	(0.1)	0.6	0.2	1.0	0.4	0.5	0.7	(0.0)	0.3	0.3	0.2	0.1	0.3	[redacted]														
		Scope 2	0.4	0.5	0.2	0.2	1.0	0.3	0.0	0.1	(0.1)	0.4	0.3	0.2	0.6	0.4	0.1	0.0	0.3	0.3	0.3	0.3	0.4	[redacted]														
		Scope 3	0.5	0.3	0.6	0.4	0.3	1.0	(0.0)	(0.0)	(0.1)	0.5	0.5	0.4	0.9	0.5	0.3	(0.0)	0.5	0.6	0.4	0.3	0.4	[redacted]														
	Growth Rate	Scope 1	(0.0)	(0.0)	(0.1)	0.0	0.0	(0.0)	1.0	0.5	0.6	(0.0)	(0.1)	0.0	(0.0)	(0.0)	(0.0)	0.6	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	[redacted]														
		Scope 2	(0.0)	0.0	(0.1)	0.0	0.1	(0.0)	0.5	1.0	0.6	(0.0)	(0.0)	0.0	0.0	(0.0)	0.0	0.5	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	[redacted]														
		Scope 3	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	0.6	0.6	1.0	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)	(0.0)	0.6	(0.1)	(0.0)	(0.1)	(0.0)	(0.1)	[redacted]														
	Log Monetary Value	Direct	1.0	0.7	0.8	0.6	0.4	0.5	(0.0)	(0.0)	(0.1)	1.0	0.8	0.6	0.6	0.8	0.4	(0.0)	0.8	0.4	0.7	0.7	0.4	[redacted]														
		Indirect	0.8	0.9	1.0	0.2	0.3	0.5	(0.1)	(0.0)	(0.1)	0.8	1.0	0.2	0.6	0.8	0.2	(0.1)	0.9	0.3	0.8	0.8	0.3	[redacted]														
	Impact Ratio	Direct	0.6	0.1	0.2	1.0	0.2	0.4	0.0	0.0	(0.1)	0.6	0.2	1.0	0.4	0.5	0.7	(0.0)	0.3	0.3	0.2	0.1	0.3	[redacted]														
		Indirect	0.6	0.4	0.5	0.4	0.6	0.9	(0.0)	0.0	(0.1)	0.6	0.6	0.4	1.0	0.5	0.3	(0.0)	0.5	0.6	0.4	0.3	0.5	[redacted]														
Water	Log Total Value		0.8	0.7	0.7	0.5	0.4	0.5	(0.0)	(0.0)	(0.1)	0.8	0.8	0.5	0.5	1.0	0.6	0.0	0.8	0.5	0.7	0.7	0.4	[redacted]														
	Intensity		0.4	(0.0)	0.2	0.7	0.1	0.3	(0.0)	0.0	(0.1)	0.4	0.2	0.7	0.3	0.6	1.0	0.0	0.3	0.5	0.1	0.1	0.2	[redacted]														
	Growth Rate		(0.0)	(0.0)	(0.1)	(0.0)	0.0	(0.0)	0.6	0.5	0.6	(0.0)	(0.1)	(0.0)	(0.0)	0.0	0.0	1.0	(0.0)	0.0	(0.0)	(0.0)	(0.0)	[redacted]														
	Log Monetary Value		0.8	0.8	0.9	0.3	0.3	0.5	(0.1)	(0.0)	(0.1)	0.8	0.9	0.3	0.5	0.8	0.3	(0.0)	1.0	0.5	0.8	0.8	0.3	[redacted]														
	Impact Ratio		0.4	0.2	0.3	0.3	0.3	0.6	(0.0)	(0.0)	(0.0)	0.4	0.3	0.3	0.6	0.5	0.5	0.0	0.5	1.0	0.3	0.2	0.4	[redacted]														
Waste	Log Total Value	Landfill	0.7	0.8	0.8	0.2	0.3	0.4	(0.0)	(0.0)	(0.1)	0.7	0.8	0.2	0.4	0.7	0.1	(0.0)	0.8	0.3	1.0	0.9	0.6	[redacted]														
		Incineration	0.7	0.8	0.8	0.1	0.3	0.3	(0.0)	(0.0)	(0.0)	0.7	0.8	0.1	0.3	0.7	0.1	(0.0)	0.8	0.2	0.9	1.0	0.4	[redacted]														
	Intensity	Landfill	0.4	0.3	0.3	0.3	0.4	0.4	(0.0)	(0.0)	(0.1)	0.4	0.3	0.3	0.5	0.4	0.2	(0.0)	0.3	0.4	0.6	0.4	1.0	[redacted]														
		Incineration	0.2	0.2	0.1	0.0	0.4	0.3	0.0	0.0	0.0	0.3	0.2	0.0	0.3	0.3	0.1	0.1	0.3	0.3	0.3	0.5	0.5	[redacted]														
	Growth Rate	Landfill	(0.0)	(0.0)	(0.1)	(0.0)	0.0	(0.0)	0.5	0.5	0.6	(0.0)	(0.1)	(0.0)	(0.0)	(0.0)	(0.0)	0.6	(0.0)	(0.0)	0.0	0.0	0.1	[redacted]														
		Incineration	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	0.6	0.5	0.7	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	(0.0)	0.6	(0.0)	(0.0)	(0.0)	0.0	(0.0)	[redacted]														
	Log Monetary Value	Landfill	0.8	0.8	0.8	0.3	0.3	0.4	(0.1)	(0.0)	(0.1)	0.8	0.9	0.3	0.4	0.8	0.3	(0.0)	0.9	0.3	1.0	0.9	0.5	[redacted]														
		Incineration	0.7	0.9	1.0	0.1	0.2	0.4	(0.1)	(0.1)	(0.1)	0.7	1.0	0.1	0.4	0.7	0.1	(0.1)	0.9	0.2	0.8	0.8	0.2	[redacted]														
	Impact Ratio	Landfill	0.5	0.2	0.3	0.5	0.3	0.4	(0.0)	0.0	(0.1)	0.5	0.3	0.5	0.4	0.5	0.5	(0.0)	0.4	0.4	0.4	0.3	0.8	[redacted]														
		Incineration	0.4	0.4	0.5	0.1	0.5	0.8	(0.0)	(0.0)	(0.1)	0.4	0.5	0.1	0.8	0.4	0.0	(0.0)	0.5	0.5	0.3	0.3	0.5	[redacted]														
Land & Water Pollutants	Log Monetary Value		0.8	0.8	0.9	0.3	0.3	0.6	(0.1)	(0.0)	(0.1)	0.8	0.9	0.3	0.6	0.8	0.3	(0.1)	1.0	0.5	0.8	0.8	0.3	[redacted]														
	Impact Ratio		0.4	0.2	0.3	0.3	0.2	0.6	(0.0)	(0.0)	(0.0)	0.4	0.3	0.3	0.6	0.5	0.4	(0.0)	0.5	0.9	0.3	0.2	0.3	[redacted]														
Air Pollutants	Log Monetary Value	Direct	0.9	0.7	0.8	0.5	0.4	0.6	(0.0)	(0.0)	(0.1)	0.9	0.8	0.5	0.6	0.8	0.4	(0.0)	0.8	0.4	0.7	0.7	0.4	0.3	(0.0)	(0.0)	0.8	0.7	0.5	0.5	0.8	0.4	1.0	0.8	0.6	0.6	0.8	0.5
		Indirect	0.8	0.9	1.0	0.2	0.3	0.5	(0.1)	(0.1)	(0.1)	0.8	1.0	0.2	0.5	0.7	0.1	(0.1)	1.0	0.4	0.8	0.8	0.3	0.2	(0.1)	(0.0)	0.9	1.0	0.3	0.5	0.9	0.4	0.8	1.0	0.2	0.5	0.9	0.3
	Impact Ratio	Direct	0.5	0.1	0.2	0.8	0.3	0.4	(0.0)	0.0	(0.1)	0.5	0.2	0.8	0.4	0.5	0.6	(0.0)	0.3	0.4	0.2	0.1	0.3	0.1	(0.0)	(0.0)	0.3	0.1	0.5	0.2	0.3	0.4	0.6	0.2	1.0	0.4	0.4	0.6
		Indirect	0.5	0.4	0.5	0.2	0.5	0.9	(0.0)	(0.0)	(0.1)	0.5	0.5	0.2	0.9	0.5	0.2	(0.0)	0.5	0.7	0.4	0.3	0.5	0.4	(0.0)	(0.0)	0.4	0.4	0.4	0.9	0.5	0.7	0.6	0.5	0.4	1.0	0.5	0.4
Natural Resource Use	Log Monetary Value		0.8	0.8	0.9	0.4	0.3	0.5	(0.1)	(0.1)	(0.1)	0.8	0.9	0.4	0.5	0.8	0.3	(0.1)	0.9	0.3	0.8	0.7	0.3	0.2	(0.1)	(0.1)	0.8	0.9	0.3	0.4	0.9	0.3	0.8	0.9	0.4	0.5	1.0	0.5
	Impact Ratio		0.5	0.2	0.3	0.7	0.4	0.5	(0.0)	0.0	(0.1)	0.5	0.3	0.7	0.5	0.5	0.5	(0.0)	0.3	0.4	0.2	0.1	0.3	0.1	(0.0)	(0.0)	0.3	0.2	0.4	0.3	0.3	0.3	0.5	0.3	0.6	0.4	0.5	1.0

matrixes, green cells represent positive correlations and red cells represent negative correlations. Darker background colors indicate larger magnitudes of correlation.

We observe that most of our environmental measures are positively correlated, and the correlations within each category (carbon, water, waste, etc.) are greater than those between different categories. In particular, the logarithms and growth rates of carbon emissions in different Scope classifications are highly correlated, with correlation coefficients generally greater than 0.6. This implies that there is considerable overlap in information between these different environmental measures. Consequently, one may expect similar performance from portfolios constructed from using these different measures, which we demonstrate later in the Water, Waste, and Other Green Portfolios section.

Conversely, growth rates show a low correlation with other measures, with coefficients between –0.1 and +0.1. In particular, most growth rates have a slight negative correlation with other measures, which implies that companies with higher levels of emissions are growing at slower rates than companies with lower levels of emissions.

PORTFOLIO CONSTRUCTION

In this section, we outline several different methods to construct impact portfolios based on the environmental data. In particular, we first introduce the optimal impact portfolio construction framework proposed by Lo and Zhang (2021) and then describe several specific long-only and long–short impact portfolios that we subsequently test.

Optimal Impact Portfolio Weights

Here, we briefly review the impact portfolio construction framework first proposed by Lo and Zhang (2021).[14] Denote by N the number of assets in the portfolio, θ_i the *residual return* of asset i from an asset pricing model (the Fama–French five-factor model in our case), and X_i a specific environmental measure (e.g., the logarithm of Scope 1 carbon emissions) for asset i. Let $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_N)^\top$ and $\boldsymbol{X} = (X_1, X_2, \ldots, X_N)^\top$. We also refer to $\boldsymbol{X}$ as the *impact variable*. Impact investors will rank securities according to the impact variable, $\boldsymbol{X}$, and we denote by $\theta_{[i:N]}$ the residual return of the i-th ranked asset.[15] The optimal weights of these $\boldsymbol{X}$-ranked assets are given by (Lo and Zhang 2021; Lo et al. 2022):

$$\propto \Sigma^{-1}\boldsymbol{\mu}, \tag{1}$$

where $\boldsymbol{\mu}$ and Σ are the expected value and covariance matrix of the residual returns of ranked securities, $(\theta_{[1:N]}, \theta_{[2:N]}, \ldots, \theta_{[N:N]})$, and their specific values are given by

$$\mathbb{E}(\theta_{[i:N]}) = \sigma_\theta \cdot \rho \cdot \mathbb{E}(Y_{i:N}), \tag{2}$$

$$\mathrm{Var}(\theta_{[i:N]}) = \sigma_\theta^2 \cdot (1 - \rho^2 + \rho^2 \cdot \mathrm{Var}(Y_{i:N})), \tag{3}$$

$$\mathrm{Cov}(\theta_{[i:N]}, \theta_{[j:N]}) = \sigma_\theta^2 \cdot \rho^2 \cdot \mathrm{Cov}(Y_{i:N}, Y_{j:N}), \tag{4}$$

[14] See also Lo et al. (2022), which generalizes the framework to allow for general return distributions and dependence structures.

[15] These indirectly ranked statistics are called *induced order statistics*, which are random variables that are ranked not by their own values ($\boldsymbol{\theta}$ in our case) but by the values of other random variables ($\boldsymbol{X}$ in our case). They are also referred to as *concomitants* of the order statistics of $\boldsymbol{X}$ (David 1973).

for i, $j = 1, 2, \ldots, N$, and $i \neq j$. Here ρ is the correlation between $\boldsymbol{X}$ and $\boldsymbol{\theta}$, which are assumed to be jointly normally distributed, σ_θ is the standard deviation of $\boldsymbol{\theta}$, and $Y_{1:N} < Y_{2:N} < \cdots < Y_{N:N}$ are the order statistics of N independent and identically distributed standard Gaussian random variables.

Furthermore, if we approximate the covariance matrix Σ by a diagonal matrix,[16] we have the following Treynor–Black weights:

$$ {}_i \propto \frac{\mathbb{E}(\theta_{[i:N]})}{\mathrm{Var}(\theta_{[i:N]})}. \tag{5} $$

Equation 5 implies that the optimal Treynor–Black weights are determined by the first two moments of residual returns of ranked securities, which are further determined by ρ and σ_θ. We estimate these parameters as follows.

First, we estimate the residual return time series for each stock, θ_i, by running a rolling-window Fama–French five-factor regression using monthly returns for the five years preceding time .

Second, we estimate ρ and σ_θ for each year. In order to do that, we calculate ρ by calculating the cross-sectional correlation coefficient between the monthly residual returns and *las ear*'s impact factor.[17] The one-year lag between the residual returns, $\boldsymbol{\theta}$, and the impact factor, $\boldsymbol{X}$, is used for two reasons: First, the impact factors, $\boldsymbol{X}$, in the Trucost Environmental data are only updated annually, and second, investors can use only the impact factors that have already been announced to construct impact portfolios. In addition, for each month, σ_θ is calculated by the cross-sectional stanpMC 19 (e

Equal-Weighted Exclusion Implementation. We go long the top 50% of stocks as ranked by their impact score using equal weights and exclude the bottom 50% of stocks. We denote this portfolio by "EX" for simplicity.

Treynor–Black Portfolio. For each year, if the estimated correlation $\rho > 0$, we go long green stocks in the top half of impact scores using Treynor–Black weights (Equation 5). If the estimated $\rho \le 0$, we go long the top 50% of stocks using equal weights, which reduces to the EX portfolio. The weights of the bottom 50% of stocks are zero. We denote this portfolio by "TB" for simplicity.

Constrained Optimization Portfolio. For each year, we consider the following constrained mean–variance optimization problem:[18]

$$\max \quad \boldsymbol{w}^{\top}\hat{\mu} - \frac{\lambda}{2}\boldsymbol{w}^{\top}\hat{\Sigma}\boldsymbol{w} \tag{6}$$

$$\text{subject to} \quad \begin{cases} \sum_{i=1}^{N} w_i = 1, \\ w_i \ge 0, \quad i = 1, 2, \ldots, N, \\ w_i \le c, \quad i = 1, 2, \ldots, N, \\ \sum_{i=1}^{N} w_i X_{i:N} \ge \delta, \end{cases} \tag{7}$$

where $\hat{\mu}$ and $\hat{\Sigma}$ are the expected value and covariance matrix of residual returns, $\boldsymbol{\theta}$, estimated from the last five years of data; λ is the risk-aversion tuning parameter, which without loss of generality is set to be one; c is the maximum weight for each stock, which is set to be 1% for the United States and 5% for China in our empirical analysis;[19] and δ is the threshold that controls the minimum average level of impact for the portfolio. In contrast with the TB and EX portfolios, the constrained optimization portfolio does not always invest in only the top 50% of stocks. We consider two such portfolios whose level of impact, δ, is set to equal that of the long-only TB and EX portfolios, respectively, and we denote these two portfolios by "CO_{TB}" and "CO_{EX}" for simplicity.

Long–Short Portfolios

Like the long-only portfolios, for each year, we first estimate the parameters ρ and σ_{θ}. For each long–short portfolio, we require that $\Sigma_{i=1}^{N} |w_i| = 1$.

Equal-Weighted Long–Short Portfolio. For each year, we simply go long the top 50% of stocks with equal weights and short the bottom 50% of stocks with equal weights. We denote this portfolio by "EW" for simplicity.

Treynor–Black Portfolio. For each year, if the estimated correlation $\rho > 0$, we go long green stocks in the top half of impact scores and short brown stocks in the bottom half of impact scores, all using Treynor–Black weights (Equation 5). If the estimated $\rho \le 0$, we go long the top 50% of stocks with equal weights and short the bottom 50% of stocks with equal weights, which reduces to the EW portfolio. We denote this portfolio by "TB" for simplicity.

Constrained Optimization Portfolio. For each year, we consider the following constrained mean–variance optimization problem:[20]

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[18] This is a typical quadratic programming problem that can be solved by commonly used solvers. We solve this problem using Gurobi, see https://www.gurobi.com.

[19] This is because numerically more US stocks are available in our dataset than Chinese stocks. See Exhibit 1.

[20] This optimization problem is nonconvex due to the full investment constraint, $\Sigma_{i=1}^{N} |w_i| = 1$. We discuss the details for solving this problem in Appendix B of the online appendix.

$$\max \quad \boldsymbol{w}^{\mathsf{T}}\hat{\mu} - \frac{\lambda}{2}\boldsymbol{w}^{\mathsf{T}}\hat{\Sigma}\boldsymbol{w}, \tag{8}$$

$$\text{subject to} \quad \begin{cases} \sum_{i=1}^{N} |\ \ _i| = 1, \\ \sum_{i=1}^{N} \ \ _i = 0, \\ |\ \ _i| \leq c, \quad i = 1, 2, \ldots, N, \\ \sum_{i=1}^{N} \ \ _i X_{i:N} \geq \ \ , \end{cases} \tag{9}$$

where $\hat{\mu}$, $\hat{\Sigma}$, λ, c, and   are defined as in the Long-Only Portfolios section. In contrast, with the equal-weighted and Treynor–Black long–short portfolios, the constrained optimization portfolio may not only go long the top 50% of stocks and short the bottom 50% of stocks. The constraint $\Sigma_{i=1}^{N} \ \ _i = 0$ ensures that the portfolio is self-financing, and the constraint $\Sigma_{i=1}^{N} \ \ _i X_{i:N} \geq$ guarantees the minimum level of the portfolio impact. We consider two such portfolios whose level of impact, , is set to equal that of the long–short TB and EW portfolios, respectively, and we denote these two portfolios by "CO_{TB}" and "CO_{EW}" for simplicity.

PERFORMANCE OF LOW-CARBON PORTFOLIOS

In this section, we focus on the US market. We discuss the performance of impact portfolios constructed based on their level of carbon emissions and analyze their factor exposures and sources of excess returns.

Correlation between Carbon Emissions and Returns

We first study the cross-sectional correlation, ρ, between the negative values of carbon emission measures (their impact factor, $\boldsymbol{X}$, in our notation) and the residual returns of stocks, $\boldsymbol{\theta}$. Exhibit 8 shows the summary statistics for the monthly time series of ρ, estimated from residual returns each month, and the one-year lagged carbon-related measures as outlined in the Optimal Impact Portfolio Weights section for US companies from 2006–2021. The average ρ's are positive for all measures, which implies that, in our sample, holding green stocks with lower-than-average carbon emissions can bring superior performance to investors.

Exhibit 8 also shows that the average values of ρ for the logarithm and growth rate of carbon emissions are higher than those for other measures, and their standard deviations are lower. This implies that the "greenness signals" derived from these measures are stronger than those derived from the carbon intensity, monetary value, or impact ratio. However, although the logarithm and growth rate of carbon emissions have stronger greenness signals, their autocorrelations are also lower, which may lead to greater turnover and difficulties in estimating ρ using historical data.

Comparing carbon emissions from different scopes, the measures related to Scope 1 and 2 emissions generally show higher correlations than those related to Scope 3. This is consistent with Cheema-Fox et al.'s (2021a) findings and may be due to the fact that both Scope 1 and 2 emissions are easier to measure and have stricter disclosure requirements (Bolton and Kacperczyk 2021a). Therefore, using Scope 1 and 2 data may bring better portfolio performance.

EXHIBIT 8

Summary Statistics for the Monthly Time Series of Cross-Sectional Correlation, ρ, for Carbon-Related Measures in US Companies

Portfolio Performance

For each carbon-related measure, we form both long-only and long–short portfolios as outlined in the Portfolio Construction section. In each year, we estimate the parameters (ρ and σ_θ) based on data from the past five years and update the portfolio weights accordingly. In this way, we test the profitability of all strategies from 2011–2021.[21]

Scope 1, 2, and 3 Log Emission. Exhibit 9 summarizes the performance of portfolios constructed using the logarithms of Scope 1, Scope 2, and Scope 3 carbon emissions.[22] In particular, we report their annualized return (return), standard deviation (std.), Sharpe ratio (SR), alpha from the Fama–French five-factor model (α), volatility of active returns ($\sigma(\theta_p)$), information ratio (IR), maximum drawdown (MDD), and annual turnover.[23] In addition, Exhibit 10 visualizes the cumulative residual returns for these portfolios using the logarithm of carbon emissions as their impact measures.

[21] The environmental data start in 2005, which we use to correlate with the residual returns starting in 2006. By the end of 2010, we have five years of data to estimate ρ.

[22] We take the natural logarithm of emission levels following Bolton and Kacperczyk (2021a), which makes the distribution of the emission measure closer to normal. This helps to improve the empirical estimation of ρ. In fact, Lo et al. (2022) prove that the performance of green portfolios depends only on the *rank* of impact factors, which is invariant under the logarithmic transformation.

[23] We define the maximum drawdown as

$$\text{MDD} = \max_{0 \le \tau_1 \le \tau_2 \le T} (Y_{\tau_1} - Y_{\tau_2}),$$

where Y_t is the cumulative log return from time 0 through t, and define the annual turnover as

$$\text{turnover} = \frac{1}{T}\sum_{t=1}^{T}\left(\sum_{i=1}^{N}\left|\omega_{i,t+1} - \frac{\omega_{i,t}(1+r_{i,t+1})}{1+\sum_{j=1}^{N}\omega_{j,t}\, r_{j,t+1}}\right|\right),$$

where $\omega_{i,t}$ and $r_{i,t}$ are the weight and return of stock i in the portfolio in year t, respectively. The portfolio alpha, α, is the intercept terms from the Fama–French five-factor regression (see also the Factor Exposures section), and the volatility of active returns, $\sigma(\theta_p)$, is the standard deviation of the regression's residual returns. The information ratio is defined as the ratio of α to $\sigma(\theta_p)$.

EXHIBIT 9

Performance of Impact Portfolios Constructed Using the Logarithm of Carbon Emissions

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Scope 1									
Return	15.84%	15.97%	13.37%	14.44%	15.22%	1.03%	0.75%	–3.94%	–4.51%
Std.	19.00%	18.42%	17.27%	17.73%	18.39%	4.54%	3.17%	13.61%	15.04%
SR	0.83	0.86	0.77	0.81	0.82	0.20	0.20	–0.30	–0.31
α	3.63%	2.85%	2.40%	1.91%	0.56%	2.38%	1.78%	–0.54%	–1.61%
$\sigma(\theta_p)$	5.46%	4.47%	5.19%	5.10%	3.89%	3.06%	2.13%	11.30%	12.28%
IR	0.67	0.64	0.46	0.37	0.14	0.78	0.83	–0.05	–0.13
MDD	76.29%	85.44%	81.43%	72.62%	85.86%	17.35%	10.47%	77.65%	90.98%
Turnover	36.02%	35.18%	75.74%	87.83%	27.35%	41.72%	43.99%	110.28%	121.21%
Impact	1.20	0.78	1.20	0.78	0.00	1.25	0.78	1.25	0.78
Scope 2									
Return	16.05%	15.79%	13.70%	14.53%	15.23%	0.66%	0.56%	–3.95%	–6.48%
Std.	19.08%	18.48%	16.98%	17.53%	18.40%	4.36%	3.02%	12.33%	15.76%
SR	0.84	0.85	0.80	0.82	0.82	0.12	0.15	–0.33	–0.42
α	4.12%	2.88%	2.83%	1.73%	0.56%	2.39%	1.81%	–0.02%	–2.59%
$\sigma(\theta_p)$	5.95%	4.60%	5.04%	5.03%	3.89%	2.67%	1.82%	10.01%	13.07%
IR	0.69	0.63	0.56	0.34	0.14	0.89	0.99	0.00	–0.20
MDD	78.09%	85.78%	77.60%	70.53%	85.81%	17.48%	11.83%	65.77%	98.23%
Turnover	44.13%	37.17%	78.53%	85.29%	27.35%	50.57%	46.16%	115.37%	123.70%
Impact	1.25	0.79	1.25	0.79	0.00	1.21	0.79	1.21	0.79
Scope 3									
Return	15.38%	14.96%	12.47%	13.96%	15.23%	0.28%	–0.26%	–3.10%	–4.70%
Std.	19.47%	18.78%	17.63%	17.77%	18.39%	4.52%	2.93%	12.82%	14.27%
SR	0.78	0.79	0.70	0.78	0.82	0.04	–0.13	–0.25	–0.34
α	2.83%	1.81%	1.13%	1.42%	0.56%	1.46%	0.73%	0.25%	–0.89%
$\sigma(\theta_p)$	6.38%	4.65%	6.05%	5.58%	3.89%	2.93%	1.73%	9.89%	11.21%
IR	0.44	0.39	0.19	0.25	0.14	0.50	0.42	0.02	–0.08
MDD	76.27%	81.94%	60.09%	67.01%	85.82%	17.36%	9.11%	65.57%	80.09%
Turnover	43.14%	36.07%	82.82%	85.83%	27.35%	50.56%	44.58%	114.28%	124.19%
Impact	1.09	0.80	1.09	0.80	0.00	1.08	0.80	1.08	0.80

NOTE: All results in this exhibit are annualized.

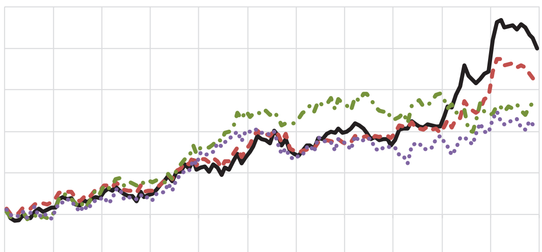
For long-only portfolios, TB achieves the highest alphas among all strategies. The annualized alphas of TB long-only portfolios are 3.63%, 4.12%, and 2.83%, for Scope 1, Scope 2, and Scope 3 log emissions, respectively, all of which are greater than those of other long-only portfolios (e.g., 2.85%, 2.88%, and 1.81%, for the EX portfolios). TB long-only portfolios also achieve the highest information ratios (0.67, 0.69, and 0.44, for Scopes 1, 2, and 3, respectively). Among the five long-only portfolios, the equal-weighted long-all portfolio has the lowest alpha and information ratio,[24] which is consistent with our finding in the Correlation between Carbon Emissions and Returns section that low-emission stocks are positively correlated with residual returns. The long-only constrained optimization portfolios, CO_{TB} and CO_{EX}, generally

[24] The results of the long-all portfolios are not exactly the same for different environmental measures, because for each measure, these portfolios invest only in stocks with valid data for that measure. Therefore, the investable universes for different measures are slightly different.

EXHIBIT 10

Cumulative Residual Returns for Long-Only and Long–Short US Impact Portfolios Constructed Using Logarithm of Carbon Emissions

Panel A: Scope 1, Long Only



Panel B: Scope 1, Long–Short

Panel C: Scope 2, Long Only

Panel D: Scope 2, Long–Short

Panel E: Scope 3, Long Only

Panel F: Scope 3, Long–Short

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outperform the long-all portfolio but underperform the long-only EX and TB portfolios. This highlights the difficulty of using mean–variance optimization in practice to construct impact portfolios without a good return and covariance forecast and demonstrates the robustness of the impact investing framework of Lo and Zhang (2021) based on Treynor–Black weights.

For long–short portfolios, TB also achieves the highest alphas across all three log emission measures (2.38%, 2.39%, and 1.46%, for Scope 1, 2, and 3, respectively). This further demonstrates the robustness of the Lo and Zhang (2021) portfolios in practice. However, the long–short constrained optimization portfolios, CO_{TB} and CO_{EW}, perform poorly and show large swings of cumulative active returns. They both gain negative returns and alphas at the end of our sample period. We will see in the next section that this high volatility in active returns is due to the fact that the long–short constrained optimization portfolios usually have large (negative) exposures to market returns.

Overall, portfolios constructed based on Scope 1 and 2 emissions have both higher alphas and higher information ratios compared to portfolios based on Scope 3 emissions. This is consistent with our finding in the Correlation between Carbon Emissions and Returns section that Scope 1 and 2 emissions have stronger signals for returns than Scope 3 emissions.

In addition to financial performance, Exhibit 9 also reports the average impact scores of each portfolio—in this case, the average of the negative log carbon emissions—which is defined as

$$\frac{\sum_{i=1}^{N} \; {}_{i} X_{i:N} - \bar{X}}{\sigma(X)},$$

where $\bar{X} = \Sigma_{i=1}^{N} X_{i:N} \; / \; N$ and $\sigma(X) = \sqrt{\Sigma_{i=1}^{N} (X_{i:N} - \bar{X})^2 \; / \, (N-1)}$ represent the sample mean and standard deviation of the cross-sectional greenness impact scores, respectively. Therefore, by definition, the average impact scores of equal-weighted long-all portfolios are zero. For long-only portfolios, the average impact scores of TB portfolios are 1.20, 1.25, and 1.09 for Scope 1, Scope 2, and Scope 3, respectively, which are all greater than those found for the EX portfolios (0.78, 0.79, and 0.80). The same results also hold for the long–short portfolios. In this sense, the Treynor–Black portfolios are doing well by doing good, by not only earning better risk-adjusted returns, but also achieving higher impact through lower average carbon emissions of the portfolios. As a comparison, although the constrained optimization portfolios can flexibly choose the desired level of impact, it is difficult to achieve the same level of financial performance, at least without a good forecast of asset returns and their covariance matrix.

Other Measures of Scope 1 Emission. Log emissions measure the level of total emissions of a business. However, the information on the carbon impact of a business may be incorporated into its asset prices in different ways.[25] Here we turn to other carbon-related measures and focus on Scope 1 emissions. Exhibit 11 shows performance metrics for both long-only and long–short US impact portfolios constructed using the intensity, growth rate, monetary value, and impact ratio of Scope 1 emissions. In addition, Exhibit 12 visualizes the cumulative residual returns for these portfolios using different measures of Scope 1 carbon emissions as impact measures.

Like the portfolios based on log carbon emissions, all TB long-only and long–short portfolios achieve similar or higher alphas and information ratios compared to their corresponding long-only EX and long–short EW portfolios. In addition, TB portfolios also outperform constrained optimization portfolios in most cases, with only one exception, the long-only portfolio based on the growth rate of carbon emissions. This is because the autocorrelations for the growth rate of carbon emissions are generally lower than for other measures (as shown in the Correlation between Carbon Emissions and Returns section), which makes the estimation of the correlation, ρ, difficult. Overall, these results further demonstrate the robust performance of Lo and Zhang's (2021) impact portfolios based on Treynor–Black weights.

The returns of the long–short constrained optimization portfolios are very volatile, especially in 2020 and 2021, compared to other long–short portfolios, as shown by the purple and green dotted lines in both Exhibits 10 and 12. In the next section, we show that this phenomenon is due to their significant exposure to the market factor, as opposed to other long–short portfolios, which are close to market neutral.

[25] For example, Bolton and Kacperczyk (2021a) find different results when considering total emissions and emission intensity (i.e., emissions per unit of sales).

EXHIBIT 11

Performance of Impact Portfolios Constructed Using Scope 1 Carbon Emissions

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Intensity									
Return	14.91%	15.73%	14.71%	14.31%	15.23%	0.49%	0.51%	–3.97%	–4.64%
Std.	17.25%	17.50%	16.29%	16.35%	18.40%	4.01%	2.77%	14.01%	14.58%
SR	0.86	0.89	0.90	0.87	0.82	0.09	0.14	–0.29	–0.33
α	2.12%	2.02%	2.53%	1.40%	0.56%	1.33%	0.95%	–3.08%	–3.37%
$\sigma(\theta_p)$	3.42%	3.57%	4.54%	4.63%	3.89%	3.69%	2.55%	12.23%	12.51%
IR	0.62	0.57	0.56	0.30	0.14	0.36	0.37	–0.25	–0.27
MDD	88.20%	89.35%	78.78%	76.99%	85.91%	15.41%	9.55%	99.85%	99.50%
Turnover	36.46%	30.95%	81.89%	88.44%	27.35%	45.93%	42.00%	118.65%	122.35%
Impact	0.32	0.31	0.32	0.31	0.00	0.69	0.31	0.70	0.32
Growth Rate									
Return	15.42%	15.06%	16.35%	15.93%	14.88%	1.07%	0.19%	0.78%	–1.76%
Std.	19.44%	18.37%	16.10%	16.45%	18.23%	2.78%	2.01%	10.54%	12.88%
SR	0.79	0.81	1.01	0.96	0.81	0.34	0.03	0.06	–0.15
α	0.92%	0.72%	1.94%	1.52%	–0.11%	1.47%	0.32%	2.58%	0.17%
$\sigma(\theta_p)$	5.39%	4.16%	4.96%	5.34%	3.75%	2.08%	1.46%	8.46%	10.49%
IR	0.17	0.17	0.39	0.28	–0.03	0.71	0.22	0.30	0.02
MDD	80.73%	90.50%	61.76%	60.90%	85.24%	6.35%	8.08%	43.71%	66.37%
Turnover	120.71%	93.47%	144.09%	125.31%	26.13%	127.95%	104.35%	155.00%	141.41%
Impact	0.97	0.61	0.97	0.61	0.00	1.13	0.61	1.13	0.61
Log Monetary Value									
Return	15.50%	15.89%	13.74%	14.58%	15.20%	0.84%	0.70%	–3.65%	–4.52%
Std.	18.73%	18.35%	17.12%	17.75%	18.37%	4.42%	3.13%	13.45%	15.33%
SR	0.82	0.86	0.80	0.81	0.82	0.16	0.18	–0.28	–0.30
α	3.28%	2.70%	2.89%	2.20%	0.49%	2.19%	1.69%	–0.26%	–0.98%
$\sigma(\theta_p)$	5.11%	4.35%	5.00%	5.06%	3.83%	3.02%	2.13%	11.02%	12.57%
IR	0.64	0.62	0.58	0.43	0.13	0.73	0.79	–0.02	–0.08
MDD	79.58%	86.05%	85.68%	75.47%	86.38%	15.43%	10.02%	75.31%	98.30%
Turnover	35.71%	35.04%	74.70%	86.86%	27.24%	41.87%	43.89%	110.69%	123.71%
Impact	1.19	0.79	1.19	0.79	0.00	1.24	0.79	1.24	0.79
Impact Ratio									
Return	14.84%	15.75%	14.74%	14.27%	15.22%	0.41%	0.54%	–4.17%	–4.78%
Std.	17.25%	17.53%	16.26%	16.36%	18.40%	3.99%	2.76%	13.90%	14.76%
SR	0.85	0.89	0.90	0.86	0.82	0.07	0.15	–0.31	–0.33
α	2.10%	2.07%	2.58%	1.35%	0.57%	1.28%	0.98%	–3.06%	–3.31%
$\sigma(\theta_p)$	3.41%	3.61%	4.49%	4.62%	3.91%	3.65%	2.53%	12.05%	12.59%
IR	0.62	0.57	0.57	0.29	0.15	0.35	0.39	–0.25	–0.26
MDD	87.79%	89.69%	78.20%	77.59%	85.97%	15.16%	9.27%	99.88%	100.22%
Turnover	37.00%	30.95%	81.47%	88.29%	27.33%	46.10%	41.98%	119.49%	122.53%
Impact	0.32	0.31	0.32	0.31	0.00	0.69	0.31	0.70	0.32

NOTE: All results in this exhibit are annualized.

Factor Exposures

Here we study the Fama–French factor loadings of the impact portfolios based on carbon emission measures. In particular, we regress portfolio returns, $r_{p,}$, in excess of the risk-free rate, $r_{f,}$, on the Fama–French five factors:

$$r_{p,} - r_{f,} = \alpha + \beta_1(r_{M,} - r_{f,}) + \beta_2 \mathrm{SMB} + \beta_3 \mathrm{HML} + \beta_4 \mathrm{RMW} + \beta_5 \mathrm{CMA} + \varepsilon . \quad (10)$$

EXHIBIT 12

Cumulative Residual Returns for Each Long-Only and Long–Short US Impact Portfolio Constructed Based on Scope 1 Emission Measures

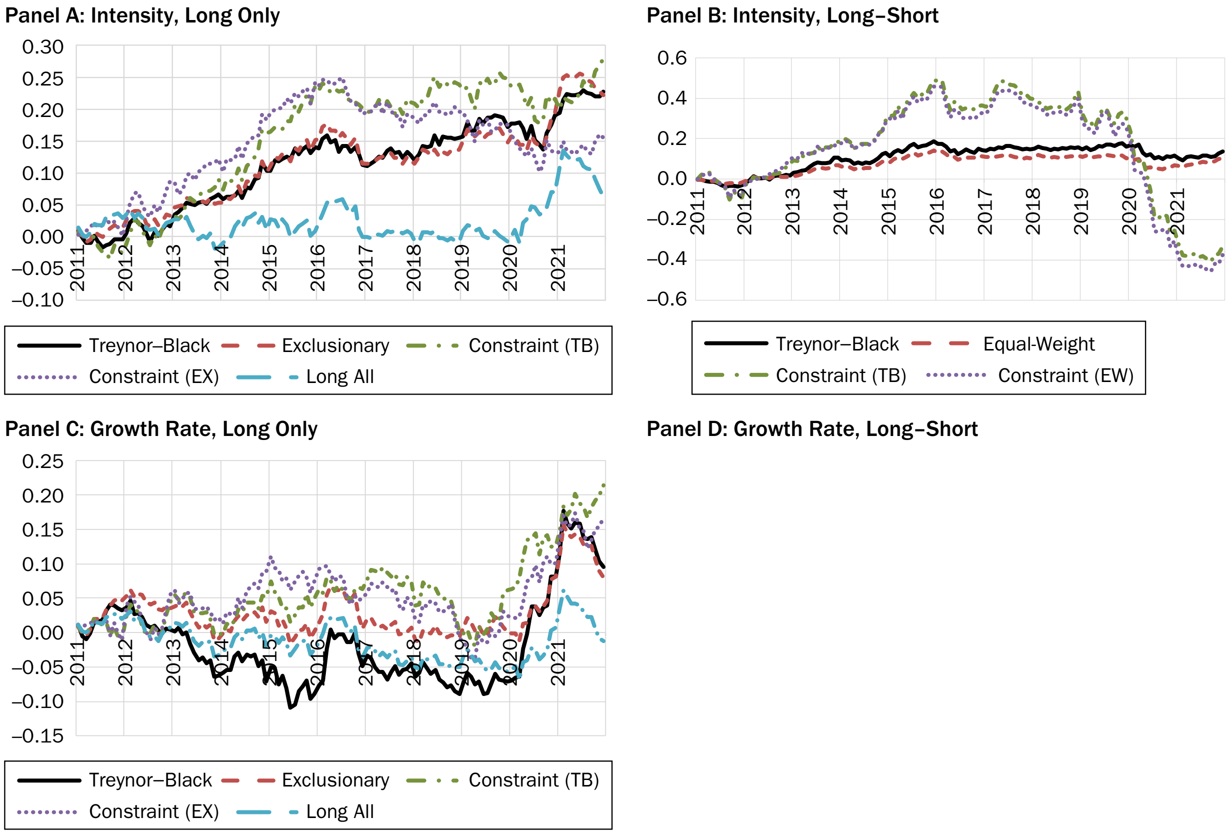


Exhibit 13 summarizes the results for US portfolios constructed based on logarithms of Scopes 1, 2, and 3 emissions. Long-only portfolios have statistically significant positive loadings on the market factor ($r_M - r_f$) and size factor (SMB) and negative loadings on the profitability factor (RMW). After controlling for these factors, the alphas are still positive, and the p-values of alphas of the TB portfolio for Scope 1 (0.055) and Scope 2 (0.053) are more significant than for Scope 3 (0.222).

For long–short portfolios, all five Fama–French factors are statistically significant, and all alphas are positive for the TB and EW portfolios. In particular, these portfolios have positive loadings on the size factor (SMB) and negative loadings on the value factor (HML), the profitability factor (RMW), and the investment factor (CMA). In addition, the long–short constrained optimization portfolios generally have larger exposures to Fama–French factors, especially the market factor. For example, the coefficients on the market factor for CO_{TB} and CO_{EW} portfolios constructed using Scope 1 emissions are –0.323 and –0.326, respectively, which are much higher in absolute value than those for the TB (–0.069) and EW portfolios (–0.062). This explains the large volatilities for constrained optimization portfolios in the Portfolio Performance section.

Exhibit 14 shows the Fama–French regression results for US portfolios constructed using other Scope 1 emission measures, including the intensity, growth rate, monetary value, and impact ratio. Like the results for the logarithms of carbon emissions, long-only portfolios show positive loadings on the size factor (SMB) and negative loadings on the profitability factor (RMW). In addition, the intensity-based and impact ratio–based long-only portfolios show positive loadings on the value factor (HML) and negative loadings on the investment factor (CMA), demonstrating that these *efficiency* metrics normalized by the total sales of a business show different characteristics than the raw emission metrics.

For long–short portfolios, most Fama–French factors can still significantly explain the returns of impact portfolios, and most portfolio alphas are positive. However, the intensity-based and impact ratio–based long–short portfolios have negative loadings on the size factor (SMB) and positive loadings on the value factor (HML), the opposite result compared to log emission-based portfolios. These results also highlight that the green portfolios constructed using environmental measures are not factor neutral.

Source of Greeniums

Our results show that green portfolios constructed using carbon-related measures for US companies gain positive excess returns (i.e., greeniums) after controlling for their Fama–French factors. This appears to be inconsistent with equilibrium theories of sustainable investing (Pástor, Stambaugh, and Taylor 2021; Pedersen, Fitzgibbons, and Pomorski 2021) and recent empirical estimates of risk premiums of high carbon emissions (Bolton and Kacperczyk 2021a, 2022). To reconcile these inconsistencies, we follow Ardia et al. (2022) and Pástor, Stambaugh, and Taylor (2022) to investigate whether unexpected shocks in climate concerns can explain these greeniums in our sample. We use the MCCC index developed by Ardia et al. (2022) as a proxy for climate concerns in the market.

We measure shocks to climate concerns as prediction errors from an AR(1) model applied to the monthly MCCC time series. Specifically, for each month , we estimate an AR(1) model using the last 36 months of MCCC data ending in month – 1, and then set the prediction error, ΔC, to be month 's realization of MCCC minus the AR(1) model's prediction. Exhibit 15A shows the original MCCC time series and the AR(1) predictions. Exhibit 15B shows the cumulative values of ΔC, which increase rapidly before 2008, decrease from 2010 through 2013, and then increase again after 2013.

EXHIBIT 13

Regression of Portfolio Excess Returns on the Fama–French Five-Factor Model

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Scope 1									
α	0.036	0.029	0.024	0.019	0.006	0.024	0.018	–0.005	–0.016
	(0.055)	(0.055)	(0.140)	(0.257)	(0.668)	(0.016)	(0.006)	(0.877)	(0.673)
$r_M - r_f$	0.953	0.997	0.854	0.939	1.060	–0.069	–0.062	–0.323	–0.326
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.000)	(0.008)	(0.010)
SMB	0.808	0.693	0.703	0.644	0.627	0.176	0.070	–0.195	–0.332
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.015)	(0.208)	(0.041)
HML	0.059	0.057	0.101	–0.128	0.122	–0.097	–0.062	–0.168	–0.169
	(0.335)	(0.275)	(0.081)	(0.029)	(0.009)	(0.000)	(0.001)	(0.137)	(0.160)
RMW	–0.385	–0.327	–0.347	–0.466	–0.072	–0.325	–0.252	–0.127	–0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.305)	(0.000)	(0.000)	(0.475)	(0.885)
CMA	–0.149	–0.105	–0.338	–0.275	0.034	–0.177	–0.139	–0.866	–0.976
	(0.286)	(0.374)	(0.007)	(0.012)	(0.717)	(0.015)	(0.002)	(0.000)	(0.000)
R^2	0.921	0.944	0.914	0.921	0.957	0.564	0.565	0.340	0.362
Scope 2									
α	0.041	0.029	0.028	0.017	0.006	0.024	0.018	0.000	–0.026
	(0.053)	(0.073)	(0.093)	(0.284)	(0.669)	(0.011)	(0.003)	(0.995)	(0.516)
$r_M - r_f$	0.925	0.980	0.837	0.931	1.061	–0.101	–0.079	–0.348	–0.376
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.004)
SMB	0.895	0.755	0.723	0.674	0.627	0.248	0.132	–0.153	–0.319
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.295)	(0.087)
HML	–0.017	0.038	0.022	–0.165	0.122	–0.117	–0.081	–0.100	–0.089
	(0.788)	(0.453)	(0.690)	(0.002)	(0.009)	(0.000)	(0.000)	(0.254)	(0.489)
RMW	–0.371	–0.305	–0.364	–0.373	–0.072	–0.285	–0.229	–0.100	–0.042
	(0.000)	(0.000)	(0.000)	(0.000)	(0.304)	(0.000)	(0.000)	(0.492)	(0.810)
CMA	–0.054	–0.034	–0.303	–0.275	0.033	–0.101	–0.068	–0.871	–1.085
	(0.740)	(0.782)	(0.005)	(0.006)	(0.718)	(0.169)	(0.170)	(0.000)	(0.002)
R^2	0.908	0.941	0.916	0.922	0.957	0.642	0.650	0.370	0.343
Scope 3									
α	0.028	0.018	0.011	0.014	0.006	0.015	0.007	0.002	–0.009
	(0.222)	(0.254)	(0.606)	(0.459)	(0.667)	(0.183)	(0.172)	(0.930)	(0.787)
$r_M - r_f$	0.965	1.000	0.854	0.922	1.060	–0.062	–0.059	–0.322	–0.374
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.003)	(0.000)	(0.002)	(0.001)
SMB	0.871	0.757	0.743	0.702	0.627	0.243	0.133	–0.107	–0.254
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.428)	(0.095)
HML	–0.054	0.045	–0.068	–0.218	0.122	–0.131	–0.074	–0.297	–0.196
	(0.458)	(0.408)	(0.415)	(0.000)	(0.009)	(0.000)	(0.000)	(0.001)	(0.043)
RMW	–0.391	–0.309	–0.388	–0.440	–0.071	–0.298	–0.235	–0.198	–0.086
	(0.000)	(0.000)	(0.000)	(0.000)	(0.309)	(0.000)	(0.000)	(0.125)	(0.531)
CMA	–0.011	–0.028	–0.390	–0.211	0.034	–0.074	–0.062	–0.818	–0.951
	(0.950)	(0.816)	(0.009)	(0.073)	(0.716)	(0.407)	(0.128)	(0.000)	(0.000)
R^2	0.898	0.942	0.888	0.906	0.957	0.596	0.663	0.430	0.409

NOTES: Portfolios are constructed using the logarithm of carbon emissions. All returns are annualized. Robust *p*-values are in parentheses.

EXHIBIT 14

Regression of Portfolio Excess Returns on the Fama–French Five-Factor Model

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO
Intensity									
α	0.021	0.020	0.025	0.014	0.006	0.013	0.009	–0.031	
	(0.025)	(0.073)	(0.051)	(0.336)	(0.666)	(0.212)	(0.178)	(0.480)	
$r_M - r_f$	0.977	1.009	0.919	0.936	1.060	–0.062	–0.050	–0.195	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.076)	(0.048)	(0.132)	
SMB	0.439	0.537	0.379	0.424	0.627	–0.105	–0.087	–0.402	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.027)	(0.008)	(0.010)	
HML	0.354	0.180	0.218	0.012	0.122	0.078	0.061	–0.098	
	(0.000)	(0.000)	(0.000)	(0.826)	(0.009)	(0.035)	(0.025)	(0.406)	
RMW	–0.172	–0.137	–0.271	–0.293	–0.071	–0.139	–0.062	0.101	
	(0.000)	(0.004)	(0.000)	(0.000)	(0.306)	(0.053)	(0.213)	(0.485)	
CMA	–0.289	–0.132	–0.444	–0.397	0.033	–0.256	–0.165	–0.744	
	(0.000)	(0.115)	(0.000)	(0.000)	(0.719)	(0.000)	(0.000)	(0.005)	
R^2	0.963	0.960	0.926	0.924	0.957	0.189	0.193	0.273	
Growth Rate									
α	0.009	0.007	0.019	0.015	–0.001	0.015	0.003	0.026	
	(0.612)	(0.613)	(0.237)	(0.411)	(0.926)	(0.041)	(0.538)	(0.305)	
$r_M - r_f$	1.101	1.057	1.004	0.987	1.074	–0.028	–0.016	–0.238	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.082)	(0.134)	(0.000)	
SMB	0.580	0.549	0.310	0.413	0.563	–0.022	–0.011	–0.392	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.397)	(0.543)	(0.000)	
HML	0.208	0.252	–0.044	–0.138	0.151	0.138	0.105	–0.041	
	(0.006)	(0.000)	(0.466)	(0.016)	(0.001)	(0.001)	(0.000)	(0.602)	
RMW	–0.209	–0.043	–0.165	–0.161	–0.028	–0.003	–0.011	0.116	
	(0.011)	(0.520)	(0.034)	(0.043)	(0.648)	(0.924)	(0.626)	(0.325)	
CMA	0.196	0.129	–0.086	–0.165	0.017	0.145	0.112	–0.470	
	(0.114)	(0.180)	(0.349)	(0.095)	(0.838)	(0.043)	(0.014)	(0.004)	
R^2	0.927	0.951	0.910	0.900	0.960	0.474	0.510	0.383	
Log Monetary Value									
α	0.033	0.027	0.029	0.022	0.005	0.022	0.017	–0.003	
	(0.051)	(0.057)	(0.068)	(0.202)	(0.699)	(0.017)	(0.007)	(0.940)	
$r_M - r_f$	0.951	0.999	0.846	0.935	1.062	–0.072	–0.061	–0.322	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.007)	
SMB	0.798	0.687	0.684	0.642	0.624	0.173	0.067	–0.199	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.017)	(0.185)	
HML	0.059	0.053	0.155	–0.086	0.122	–0.098	–0.066	–0.181	
	(0.267)	(0.287)	(0.010)	(0.133)	(0.008)	(0.000)	(0.001)	(0.114)	
RMW	–0.363	–0.319	–0.316	–0.461	–0.065	–0.313	–0.249	–0.136	
	(0.000)	(0.000)	(0.000)	(0.000)	(0.337)	(0.000)	(0.000)	(0.425)	
CMA	–0.106	–0.088	–0.388	–0.320	0.040	–0.153	–0.128	–0.864	
	(0.414)	(0.440)	(0.002)	(0.003)	(0.658)	(0.034)	(0.003)	(0.000)	
R^2	0.929	0.946	0.919	0.923	0.959	0.551	0.558	0.357	

EXHIBIT 14 *(continued)*

Regression of Portfolio Excess Returns on the Fama–French Five-Factor Model

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Impact Ratio									
α	0.021	0.021	0.026	0.014	0.006	0.013	0.010	–0.031	–0.033
	(0.026)	(0.073)	(0.044)	(0.351)	(0.663)	(0.224)	(0.157)	(0.477)	(0.457)
$r_M - r_f$	0.975	1.008	0.917	0.937	1.060	–0.062	–0.051	–0.206	–0.251
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.073)	(0.044)	(0.108)	(0.057)
SMB	0.441	0.540	0.378	0.420	0.629	–0.105	–0.085	–0.402	–0.433
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.026)	(0.008)	(0.009)	(0.007)
HML	0.356	0.183	0.220	0.015	0.122	0.081	0.064	–0.099	–0.095
	(0.000)	(0.000)	(0.000)	(0.789)	(0.009)	(0.026)	(0.016)	(0.390)	(0.425)
RMW	–0.179	–0.137	–0.267	–0.299	–0.072	–0.146	–0.060	0.078	0.157
	(0.000)	(0.004)	(0.000)	(0.000)	(0.304)	(0.041)	(0.225)	(0.581)	(0.286)
CMA	–0.291	–0.141	–0.456	–0.402	0.033	–0.260	–0.175	–0.757	–0.790
	(0.000)	(0.095)	(0.000)	(0.000)	(0.720)	(0.000)	(0.000)	(0.004)	(0.006)
R^2	0.963	0.960	0.928	0.924	0.957	0.196	0.200	0.284	0.305

NOTES: Portfolios are constructed using Scope 1 carbon emissions. All returns are annualized. Robust *p*-values are in parentheses.

We include both the monthly climate concern shocks, ΔC, and their lag-1 values, ΔC_{-1}, into the regression of portfolio returns to account for potential delays for the market to incorporate this information into asset prices:

$$r_{p,} - r_{f,} = \alpha + \beta_1 (r_{M,} - r_{f,}) + \beta_2 \mathrm{SMB} + \beta_3 \mathrm{HML} + \beta_4 \mathrm{RMW} + \beta_5 \mathrm{CMA} + \beta_6 \Delta C + \beta_7 \Delta C_{-1} + \varepsilon . \tag{11}$$

Exhibit 16 shows the estimated α, β_6, β_7, and regression R^2 for portfolios constructed using the logarithms of Scope 1, 2, and 3 carbon emissions and other Scope 1 emission measures. We include the full regression results in Appendix C of the online appendix. All regressions run from 2011–June 2018, since the MCCC data end in June 2018.

Several interesting observations can be made from the results in Exhibit 16. First, the climate concern factor can partially explain the greeniums of our impact portfolios. By comparing Exhibit 16 to Exhibits 13–14, we find that most alphas (the intercept terms) are reduced after introducing climate concerns into the regressions.[26] For example, for the TB long-only (long–short) portfolios, the alphas for portfolios constructed using logarithms of Scope 1, 2, and 3 emissions are reduced from 0.036, 0.041, and 0.028 (0.024, 0.024, and 0.015) to 0.021, 0.031, and 0.014 (0.009, 0.016, and 0.006), respectively, representing approximately 50% to 75% (38% to 67%) of the original alphas.

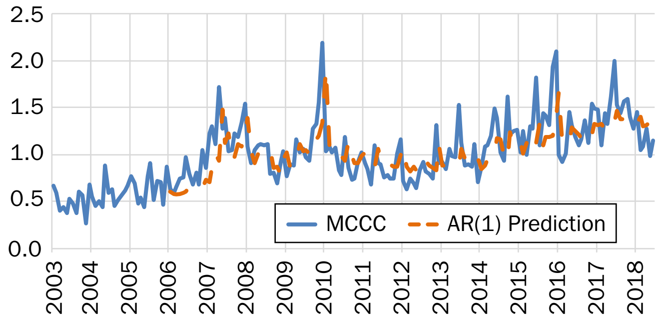
Second, an increase in climate concerns has an overall *negative* effect on Fama–French residuals. This is reflected by the negative coefficients for ΔC and ΔC_{-1} for equal-weighted long-all portfolios. Moreover, the coefficients for ΔC and ΔC_{-1} for most long-only impact portfolios are also negative, implying that this overall negative effect applies to the top half of the green stocks as well.

[26] The comparison is, strictly speaking, unfair because Exhibits 13–14 use data until 2021, while Exhibit 16 uses data only until June 2018, due to the lack of MCCC data after June 2018. However, our conclusions still hold if we run both regressions within the same time frame. For simplicity, we do not report the corresponding results for Exhibits 13–14 using data until June 2018.

EXHIBIT 15

Time Series of Original MCCC, AR(1) Prediction of MCCC, and Cumulative Values of ΔC

Panel A: MCCC and Its AR(1) Prediction



Panel B: Cumulative ΔC_t

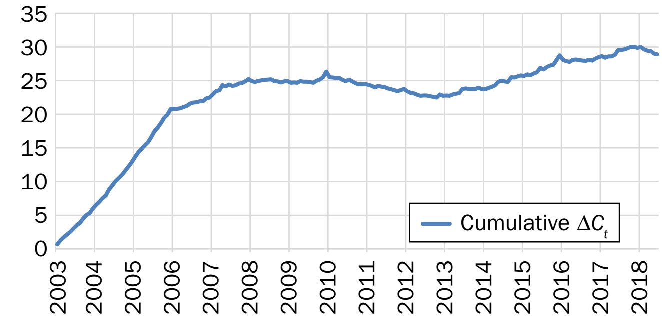


EXHIBIT 16

Regression of Portfolio Excess Returns on the Fama–French Five-Factor Model and Climate Concerns

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Scope 1 Log Emissions									
α	0.021	0.022	0.019	0.012	0.009	0.009	0.010	0.001	0.002
	(0.115)	(0.057)	(0.255)	(0.540)	(0.441)	(0.347)	(0.130)	(0.968)	(0.946)
ΔC_t	–0.044	–0.073	–0.006	–0.025	–0.096	0.057	0.026	0.031	0.007
	(0.381)	(0.120)	(0.921)	(0.727)	(0.010)	(0.087)	(0.294)	(0.763)	(0.938)
ΔC_{t-1}	–0.033	–0.002	0.027	0.056	–0.061	0.029	0.060	0.349	0.450
	(0.446)	(0.953)	(0.619)	(0.304)	(0.105)	(0.338)	(0.014)	(0.001)	(0.000)
R^2	0.941	0.954	0.919	0.907	0.958	0.476	0.448	0.438	0.470
Scope 2 Log Emissions									
α	0.031	0.026	0.025	0.014	0.009	0.016	0.014	0.008	0.013
	(0.026)	(0.034)	(0.166)	(0.459)	(0.443)	(0.021)	(0.009)	(0.747)	(0.651)
ΔC_t	–0.065	–0.083	–0.059	–0.073	–0.096	0.021	0.016	0.020	0.018
	(0.209)	(0.065)	(0.419)	(0.324)	(0.010)	(0.359)	(0.343)	(0.803)	(0.831)
ΔC_{t-1}	–0.013	–0.045	0.118	0.108	–0.061	0.030	0.018	0.343	0.427
	(0.772)	(0.215)	(0.039)	(0.053)	(0.103)	(0.196)	(0.328)	(0.000)	(0.000)
R^2	0.931	0.954	0.908	0.905	0.958	0.551	0.516	0.524	0.501
Scope 3 Log Emissions									
α	0.014	0.013	0.001	0.013	0.009	0.006	0.001	0.014	0.012
	(0.290)	(0.332)	(0.947)	(0.525)	(0.438)	(0.416)	(0.819)	(0.589)	(0.685)
ΔC_t	–0.112	–0.102	–0.084	–0.102	–0.096	–0.027	–0.003	0.005	0.029
	(0.017)	(0.025)	(0.258)	(0.183)	(0.010)	(0.214)	(0.838)	(0.951)	(0.741)
ΔC_{t-1}	–0.038	–0.046	0.143	0.109	–0.061	0.017	0.017	0.380	0.378
	(0.386)	(0.282)	(0.014)	(0.049)	(0.104)	(0.367)	(0.233)	(0.000)	(0.000)
R^2	0.946	0.950	0.882	0.889	0.958	0.557	0.601	0.516	0.519
Scope 1 Intensity									
α	0.014	0.014	0.012	0.011	0.009	0.003	0.002	0.002	0.002
	(0.240)	(0.207)	(0.408)	(0.526)	(0.438)	(0.843)	(0.843)	(0.701)	(0.701)
ΔC_t	–0.022	–0.044	–0.024	–0.036	–0.096	0.091	0.054	0.039	0.025
	(0.562)	(0.228)	(0.655)	(0.587)	(0.010)	(0.027)	(0.047)	(0.696)	(0.771)
ΔC_{t-1}	–0.014	–0.008	0.087	0.066	–0.061	0.057	0.054	0.362	0.415
	(0.722)	(0.814)	(0.120)	(0.261)	(0.105)	(0.218)	(0.092)	(0.001)	(0.000)
R^2	0.958	0.961	0.934	0.914	0.958	0.235	0.232	0.431	0.483

(con in ed)

EXHIBIT 16 *(continued)*

Regression of Portfolio Excess Returns on the Fama–French Five-Factor Model and Climate Concerns

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Scope 1 Growth Rate									
α	0.003	0.009	0.002	–0.002	0.003	0.009	0.003	0.009	0.006
	(0.862)	(0.446)	(0.895)	(0.928)	(0.785)	(0.261)	(0.622)	(0.700)	(0.807)
ΔC_t	–0.101	–0.107	–0.138	–0.176	–0.112	0.028	0.008	0.002	–0.005
	(0.017)	(0.001)	(0.023)	(0.016)	(0.000)	(0.156)	(0.544)	(0.981)	(0.949)
ΔC_{t-1}	–0.098	–0.072	0.068	0.114	–0.049	–0.031	–0.021	0.287	0.317
	(0.073)	(0.097)	(0.236)	(0.058)	(0.222)	(0.221)	(0.329)	(0.001)	(0.001)
R^2	0.931	0.955	0.905	0.894	0.961	0.476	0.458	0.365	0.411
Scope 1 Log Monetary Value									
α	0.020	0.022	0.020	0.013	0.009	0.009	0.010	0.006	0.011
	(0.118)	(0.062)	(0.234)	(0.468)	(0.443)	(0.351)	(0.151)	(0.839)	(0.721)
ΔC_t	–0.047	–0.075	–0.004	–0.013	–0.097	0.055	0.024	0.000	0.013
	(0.353)	(0.108)	(0.944)	(0.856)	(0.009)	(0.101)	(0.339)	(0.997)	(0.898)
ΔC_{t-1}	–0.032	–0.001	0.016	0.056	–0.061	0.030	0.062	0.353	0.469
	(0.462)	(0.986)	(0.764)	(0.309)	(0.105)	(0.338)	(0.013)	(0.001)	(0.000)
R^2	0.940	0.954	0.925	0.912	0.958	0.469	0.444	0.467	0.468
Scope 1 Impact Ratio									
α	0.014	0.014	0.013	0.011	0.009	0.002	0.002	0.011	0.012
	(0.224)	(0.197)	(0.388)	(0.521)	(0.433)	(0.872)	(0.824)	(0.714)	(0.695)
ΔC_t	–0.025	–0.046	–0.026	–0.038	–0.096	0.089	0.054	0.036	0.023
	(0.518)	(0.217)	(0.634)	(0.559)	(0.010)	(0.031)	(0.050)	(0.714)	(0.798)
ΔC_{t-1}	–0.023	–0.009	0.086	0.065	–0.061	0.054	0.054	0.356	0.410
	(0.560)	(0.802)	(0.125)	(0.266)	(0.103)	(0.241)	(0.094)	(0.001)	(0.000)
R^2	0.958	0.961	0.933	0.914	0.958	0.245	0.233	0.435	0.484

NOTES: Portfolios are constructed using all carbon-related measures. Both the portfolio returns and the Fama–French factor returns are in monthly time series. Robust *p*-values are in parentheses.

Third, the negative effect of climate concern shocks is smaller on green stocks than on brown stocks, and an increase in climate concern leads to positive returns for "green-minus-brown" portfolios, on average. Exhibit 16 shows that, for most long–short impact portfolios constructed using logarithms of Scope 1 and 2 emissions, intensity, monetary value, and impact ratio, the regression coefficients for both ΔC and ΔC_{-1} are positive. This is consistent with Ardia et al.'s (2022) and Pástor, Stambaugh, and Taylor's (2022) findings.

Fourth, the information in climate concern shocks is incorporated into prices slowly. Although we observe that the coefficients for ΔC are generally greater than those for ΔC_{-1} (in absolute value) and have lower *p*-values, these patterns are not particularly consistent across different portfolios. Certain portfolios have more significant lag-1 coefficients than lag-0 coefficients. This implies that both the same month's climate shock, ΔC, and the previous month's climate shock, ΔC_{-1}, have an impact on green portfolio returns.

Finally, although all carbon-related measures lead to positive greeniums in our sample, the sources of greeniums are slightly different for different measures. In particular, while the signs of coefficients for ΔC and ΔC_{-1} are consistent for portfolios constructed using most measures, their significance levels vary. For example, for long–short portfolios, coefficients for ΔC are more significant for portfolios constructed using intensity and impact ratio (*p*-values of 0.027 and 0.031, respectively, for TB portfolios).

For long-only portfolios, coefficients for ΔC are more significant for portfolios constructed using logarithms of Scope 3 carbon emissions and growth rate (p-values of both 0.017 for TB portfolios).

We note that the negative coefficients for ΔC and ΔC_{-1} in long-only portfolios in our results are different from Ardia et al.'s (2022) finding that the climate concerns have a positive effect on returns of a portfolio that are only long green stocks. There are two main reasons that drive these differences. First, Ardia et al. (2022) study companies listed in the S&P 500 Index, while our sample contains around 1,000 stocks before 2015 and close to 3,000 stocks after 2015. Second, Ardia et al. (2022) use the ASSET4/Refinitiv dataset, while we use Trucost Environmental data to construct our portfolios.[27]

WATER, WASTE, AND OTHER GREEN PORTFOLIOS

In addition to carbon-related measures, we also systematically investigate the performance and source of greeniums in green portfolios constructed using noncarbon environmental measures, including water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource use. We again focus on the US market in this section.

Exhibit 17 shows the summary statistics for the monthly time series of cross-sectional correlation, ρ, between impact factors—defined as the negative values of the environmental measures above—and the residual returns of stocks. Almost all average ρ's are positive, similar to the results for carbon-related measures (Exhibit 8). This is consistent with the fact that most environmental measures are already positively correlated, as shown in the Correlation between Environmental Measures section. Therefore, investing in stocks with low carbon emissions may not be the only way to earn excess returns in our sample. Constructing portfolios based on other environmental measures may lead to similar results.

As in the Portfolio Performance section, we also implement both long-only and long–short portfolios outlined in the Portfolio Construction section for each environmental measure. The financial performance of these portfolios is qualitatively similar to those of carbon emission measures. In particular, TB portfolios generally have the largest alphas, information ratios, and average impact scores. In contrast, the performance of portfolios constructed using growth rates is relatively poor. We report the full set of results in Appendix D of the online appendix.

We also study the source of greeniums for these portfolios by performing Fama–French five-factor regressions using the additional climate concern factors, and the results are reported in Appendix E of the online appendix. These results are similar to our findings in the Source of Greeniums section in that an increase in climate concern has an overall negative effect on the market, and the negative effect on green stocks is lower than that on brown stocks.

GREEN PORTFOLIOS IN THE CHINESE MARKET

In this section, we investigate the performance of portfolios constructed using stocks and environmental measures of companies in the Chinese market. We follow

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[27] I

EXHIBIT 17

Summary Statistics for Monthly Time Series of Cross-Sectional Correlation, ρ, for Noncarbon Environmental Measures in US Companies

		Mean	Std	Min	25%	50%	75%	Max	Autocorr
Water									
Log Total Level		0.013	0.061	–0.176	–0.027	0.011	0.055	0.154	0.223
Intensity		0.002	0.071	–0.243	–0.033	0.011	0.040	0.194	0.344
Growth Rate		0.007	0.049	–0.137	–0.025	0.012	0.042	0.100	0.127
Log Monetary Value		0.012	0.050	–0.150	–0.024	0.005	0.048	0.123	0.331
Impact Ratio		–0.001	0.054	–0.179	–0.033	0.002	0.037	0.114	0.409
Waste									
Log Total Level	Landfill	0.014	0.049	–0.122	–0.023	0.016	0.049	0.126	0.196
	Incineration	0.015	0.052	–0.129	–0.024	0.019	0.050	0.166	0.305
Intensity	Landfill	0.014	0.046	–0.102	–0.017	0.014	0.045	0.150	0.255
	Incineration	0.003	0.054	–0.106	–0.038	–0.005	0.041	0.153	0.308
Growth Rate	Landfill	0.015	0.040	–0.080	–0.014	0.017	0.045	0.115	0.170
	Incineration	0.008	0.048	–0.109	–0.027	0.009	0.047	0.128	0.152
Log Monetary Value	Direct	0.015	0.051	–0.148	–0.022	0.014	0.058	0.131	0.245
	Indirect	0.013	0.056	–0.105	–0.028	0.015	0.054	0.155	0.236
Impact Ratio	Direct	0.007	0.049	–0.145	–0.021	0.005	0.038	0.131	0.246
	Indirect	0.010	0.079	–0.228	–0.052	0.015	0.074	0.169	0.216
Land and Water Pollutants									
Log Monetary Value		0.010	0.051	–0.150	–0.024	0.007	0.045	0.121	0.363
Impact Ratio		–0.003	0.050	–0.153	–0.032	0.000	0.031	0.125	0.325
Air Pollutants									
Log Monetary Value	Direct	0.021	0.074	–0.185	–0.030	0.028	0.074	0.186	0.122
	Indirect	0.013	0.052	–0.107	–0.025	0.010	0.052	0.140	0.244
Impact Ratio	Direct	0.013	0.074	–0.235	–0.034	0.014	0.062	0.175	0.207
	Indirect	0.005	0.062	–0.172	–0.037	0.006	0.056	0.179	0.291
Natural Resource Use									
Log Monetary Value		0.021	0.056	–0.145	–0.017	0.021	0.060	0.187	0.114
Impact Ratio		0.018	0.078	–0.173	–0.032	0.019	0.080	0.173	0.258

the same portfolio construction and analysis methodology in the Portfolio Construction and Performance of Low-Carbon Portfolios sections. The only difference is that we use environmental and return data for Chinese companies, starting from 2010 for the Chinese stock market because the Trucost coverage for Chinese companies before 2010 is too low (see Exhibit 1).

Exhibits 18 and 19 show summary statistics of the ρ time series for all carbon-related and noncarbon measures from 2010–2021. In sharp contrast to the US market (Exhibits 8 and 17), the average correlations between environmental impact factors and residual returns for the Chinese market are, in most cases, *nega i e*. In addition, the magnitudes of these negative correlations are also greater than those for the US market. For example, the average correlations for logarithms of Scope 1, 2, and 3 emissions in the Chinese market are –0.032, –0.015, and –0.041, which are all greater (in absolute value) than those for the US market (0.016, 0.014, and 0.010; see Exhibit 8).

The negative correlations imply that the greeniums—that is, the excess returns for "green-minus-brown" portfolios—in the Chinese market (a representative emerging market) are likely negative in our sample period from 2010–2021. Exhibit 20 shows

EXHIBIT 18

Summary Statistics for Monthly Time Series of Cross-Sectional Correlation, ρ , for Carbon-Related Measures in Chinese Companies

		Mean	Std	Min	25%	50%	75%	Max	Autocorr
Log Total Level	Scope 1	–0.032	0.113	–0.465	–0.089	–0.033	0.029	0.263	0.087
	Scope 2	–0.015	0.102	–0.270	–0.075	–0.021	0.047	0.449	0.129
	Scope 3	–0.041	0.100	–0.407	–0.095	–0.036	0.022	0.296	0.129
Intensity	Scope 1	–0.026	0.117	–0.575	–0.074	–0.012	0.048	0.169	0.289
	Scope 2	0.006	0.144	–0.251	–0.087	–0.011	0.085	0.522	0.596
	Scope 3	–0.050	0.113	–0.441	–0.099	–0.050	0.011	0.398	0.102
Growth Rate	Scope 1	–0.012	0.116	–0.377	–0.071	–0.007	0.052	0.393	0.181
	Scope 2	0.024	0.136	–0.285	–0.054	0.001	0.078	0.597	0.435
	Scope 3	–0.011	0.112	–0.329	–0.073	–0.021	0.049	0.457	0.121
Log Monetary Value	Direct	–0.032	0.114	–0.464	–0.091	–0.030	0.034	0.271	0.100
	Indirect	–0.036	0.099	–0.350	–0.085	–0.030	0.027	0.329	0.095
Impact Ratio	Direct	–0.026	0.117	–0.575	–0.074	–0.012	0.048	0.168	0.289
	Indirect	–0.040	0.111	–0.298	–0.107	–0.054	0.027	0.472	0.128

EXHIBIT 19

Summary Statistics for Monthly Time Series of Cross-Sectional Correlation, ρ , for Noncarbon Environmental Measures in Chinese Companies

		Mean	Std	Min	25%	50%	75%	Max	Autocorr
Water									
Log Total Level		–0.015	0.100	–0.282	–0.080	–0.025	0.043	0.454	–0.005
Intensity		0.011	0.085	–0.188	–0.032	0.008	0.044	0.356	0.209
Growth Rate		–0.007	0.112	–0.304	–0.070	–0.017	0.052	0.489	0.121
Log Monetary Value		–0.033	0.098	–0.361	–0.098	–0.028	0.033	0.308	0.058
Impact Ratio		–0.014	0.106	–0.272	–0.081	–0.015	0.041	0.375	0.131
Waste									
Log Total Level	Landfill	–0.025	0.093	–0.424	–0.083	–0.019	0.035	0.309	–0.057
	Incineration	–0.023	0.093	–0.306	–0.069	–0.021	0.030	0.352	0.020
Intensity	Landfill	–0.015	0.094	–0.316	–0.066	–0.022	0.037	0.344	0.047
	Incineration	0.000	0.104	–0.195	–0.070	–0.013	0.047	0.393	0.336
Growth Rate	Landfill	–0.003	0.116	–0.336	–0.068	–0.011	0.065	0.460	0.164
	Incineration	0.002	0.115	–0.300	–0.066	–0.014	0.070	0.485	0.164
Log Monetary Value	Direct	–0.023	0.094	–0.414	–0.078	–0.019	0.039	0.327	–0.047
	Indirect	–0.036	0.101	–0.374	–0.095	–0.031	0.021	0.284	0.157
Impact Ratio	Direct	–0.011	0.097	–0.260	–0.070	–0.015	0.035	0.360	0.077
	Indirect	–0.046	0.142	–0.417	–0.136	–0.049	0.040	0.506	0.199
Land and Water Pollutants									
Log Monetary Value		–0.037	0.101	–0.367	–0.100	–0.031	0.026	0.316	0.086
Impact Ratio		–0.029	0.111	–0.352	–0.092	–0.027	0.022	0.339	0.193
Air Pollutants									
Log Monetary Value	Direct	–0.030	0.119	–0.434	–0.096	–0.026	0.040	0.281	0.071
	Indirect	–0.040	0.102	–0.384	–0.097	–0.031	0.031	0.298	0.131
Impact Ratio	Direct	–0.014	0.103	–0.428	–0.065	–0.003	0.044	0.345	0.004
	Indirect	–0.047	0.128	–0.376	–0.127	–0.045	0.021	0.481	0.156
Natural Resource Use									
Log Monetary Value		–0.022	0.107	–0.333	–0.075	–0.033	0.034	0.352	0.172
Impact Ratio		0.015	0.096	–0.302	–0.044	0.009	0.057	0.389	0.301

EXHIBIndHIBliot f al

the performance of impact portfolios constructed using the logarithms of carbon emissions.[28] The alphas for TB and EX long-only portfolios are mostly negative.[29]

These results demonstrate the costs of low-carbon investing in the Chinese stock market. For example, if impact investors exclude the top half of high-carbon companies, and go long the other half of low-carbon stocks, they will bear negative alphas (with respect to the Fama–French five factors) of –2.64%, –1.76%, and –1.89% for Scope 1, 2, and 3 carbon emissions, respectively. In addition, if impact investors construct long–short portfolios to achieve an even lower level of average carbon

[28] These metrics are based on data from 2015–2021 because we require five years of historical data to estimate the parameters for portfolio weights, as with the US market. To make a direct comparison between the United States and China, we present the portfolio performance metrics for US green portfolios from 2015–2021 (the same period as China) in Appendix I.4 of the online appendix.

[29] The TB portfolios have almost identical performance to the EX portfolios, because the two portfolios have different weights only when the estimated correlation between impact factors and residual returns is positive. See the Long-Only Portfolios and Long–Short Portfolios sections.

emission, they will bear negative alphas of –4.32%, –3.44%, and –3.57% for the three Scopes, respectively, which are approximately twice the cost of long-only portfolios.

Exhibit 21 shows the performance of impact portfolios constructed using other Scope 1 emission measures for Chinese companies. For TB long-only portfolios

EXHIBIT 21

Performance of Impact Portfolios Constructed Using Scope 1 Carbon Emissions for Chinese Companies

	Long-Only Portfolios					Long–Short Portfolios			
	TB	EX	CO_{TB}	CO_{EX}	All	TB	EW	CO_{TB}	CO_{EW}
Intensity									
Return	6.35%	6.71%	6.75%	7.46%	9.43%	–3.04%	–2.71%	–4.22%	–4.25%
Std.	24.60%	24.57%	28.49%	28.40%	23.98%	4.11%	3.99%	12.38%	12.26%
SR	0.26	0.27	0.24	0.26	0.39	–0.75	–0.69	–0.34	–0.35
α	–3.51%	–3.24%	–5.41%	–4.63%	1.66%	–5.33%	–4.92%	–4.44%	–4.46%
$\sigma(\theta_p)$	6.63%	6.58%	13.80%	13.52%	4.85%	3.50%	3.43%	11.24%	11.13%
IR	–0.53	–0.49	–0.39	–0.34	0.34	–1.52	–1.43	–0.40	–0.40
MDD	88.14%	86.22%	80.96%	78.28%	83.64%	23.80%	21.96%	32.77%	32.48%
Turnover	42.22%	37.48%	104.41%	104.30%	33.31%	54.88%	51.83%	128.31%	128.53%
Impact	0.30	0.29	0.30	0.29	0.00	0.35	0.29	0.39	0.33
Growth Rate									
Return	7.24%	8.03%	8.51%	9.26%	10.08%	–2.42%	–2.05%	–0.58%	–0.34%
Std.	24.70%	24.63%	28.54%	28.40%	23.78%	3.04%	2.95%	11.49%	11.56%
SR	0.29	0.32	0.30	0.32	0.42	–0.80	–0.70	–0.05	–0.03
α	0.37%	1.06%	1.53%	1.94%	2.53%	–1.92%	–1.47%	0.98%	1.27%
$\sigma(\theta_p)$	5.33%	5.36%	12.54%	12.47%	4.87%	2.50%	2.41%	10.41%	10.43%
IR	0.07	0.20	0.12	0.16	0.52	–0.77	–0.61	0.09	0.12
MDD	89.57%	85.21%	96.14%	92.95%	75.29%	20.41%	18.19%	27.35%	26.33%
Turnover	99.89%	96.25%	137.24%	132.58%	32.73%	103.28%	100.90%	133.43%	133.52%
Impact	0.68	0.64	0.68	0.64	0.00	0.71	0.64	0.71	0.64
Log Monetary Value									
Return	7.42%	7.42%	5.08%	5.08%	9.42%	–2.00%	–2.00%	–2.20%	–2.20%
Std.	26.02%	26.02%	29.93%	29.93%	23.98%	4.61%	4.61%	14.52%	14.52%
SR	0.28	0.28	0.17	0.17	0.39	–0.44	–0.44	–0.15	–0.15
α	–2.68%	–2.68%	–6.41%	–6.41%	1.65%	–4.35%	–4.35%	–3.44%	–3.44%
$\sigma(\theta_p)$	6.30%	6.30%	14.22%	14.22%	4.85%	2.65%	2.65%	12.39%	12.39%
IR	–0.43	–0.43	–0.45	–0.45	0.34	–1.64	–1.64	–0.28	–0.28
MDD	95.66%	95.66%	91.41%	91.41%	83.64%	22.61%	22.61%	36.62%	36.62%
Turnover	41.63%	41.63%	112.30%	112.30%	33.29%	52.67%	52.67%	123.57%	123.57%
Impact	0.77	0.77	0.77	0.77	0.00	0.77	0.77	0.77	0.77
Impact Ratio									
Return	6.40%	6.76%	6.79%	7.49%	9.44%	–2.99%	–2.67%	–4.18%	–4.23%
Std.	24.62%	24.58%	28.49%	28.40%	23.98%	4.12%	4.00%	12.38%	12.27%
SR	0.26	0.27	0.24	0.26	0.39	–0.73	–0.68	–0.34	–0.35
α	–3.46%	–3.20%	–5.34%	–4.58%	1.67%	–5.28%	–4.88%	–4.41%	–4.44%
$\sigma(\theta_p)$	6.66%	6.60%	13.80%	13.53%	4.85%	3.51%	3.44%	11.25%	11.13%
IR	–0.52	–0.48	–0.39	–0.34	0.34	–1.50	–1.42	–0.39	–0.40
MDD	87.90%	85.97%	80.89%	78.28%	83.64%	23.52%	21.72%	32.77%	32.54%
Turnover	42.47%	37.68%	104.38%	104.25%	33.30%	55.05%	51.95%	128.30%	128.55%
Impact	0.30	0.30	0.30	0.30	0.00	0.36	0.30	0.39	0.33

NOTE: All results in this exhibit are annualized.

constructed using intensity, growth rate, monetary value, and impact ratio, the alphas are –3.51%, 0.37%, –2.68%, and –3.46%, respectively. Alphas for all portfolios are negative except for the growth rate-based portfolios due to the low average correlation between the growth rates and residual returns (–0.012; see Exhibit 18).

In addition to carbon emission measures, we also systematically study the portfolio performance for other environmental measures in the Chinese market. The results, reported in Appendix F of the online appendix, are qualitatively similar to the portfolio performance results based on carbon-related measures.

We summarize the alphas for all long-only portfolios constructed using different environmental measures in Exhibit 22 for both the US and Chinese

EXHIBIT 22

Annualized Alphas of Long-Only Portfolios Constructed Using All Environmental Measures

			TB	EX	CO_{TB}	CO_{EX}	All
Panel A: US Companies							
Carbon	Log Total Level	Scope 1	3.63%	2.85%	2.40%	1.91%	0.56%
		Scope 2	4.12%	2.88%	2.83%	1.73%	0.56%
		Scope 3	2.83%	1.81%	1.13%	1.42%	0.56%
	Intensity	Scope 1	2.06%	2.02%	2.53%	1.40%	0.56%
		Scope 2	2.73%	2.12%	3.33%	1.53%	0.56%
		Scope 3	2.81%	1.95%	2.46%	1.65%	0.56%
	Growth Rate	Scope 1	0.86%	0.72%	1.95%	1.51%	–0.11%
		Scope 2	1.54%	0.93%	1.62%	1.37%	–0.12%
		Scope 3	1.56%	1.05%	0.73%	0.58%	–0.12%
	Monetary Value	Direct	3.28%	2.70%	2.89%	2.20%	0.49%
		Indirect	3.08%	1.88%	1.98%	1.23%	0.54%
	Impact Ratio	Direct	2.05%	2.05%	2.58%	1.35%	0.57%
		Indirect	3.00%	2.24%	2.89%	2.90%	0.56%
Water	Log Total Level		4.07%	2.67%	2.46%	2.07%	0.56%
	Intensity		1.82%	2.19%	2.24%	2.36%	0.56%
	Growth Rate		0.96%	0.69%	2.50%	1.32%	–0.12%
	Monetary Value		3.22%	2.23%	1.95%	1.65%	0.54%
	Impact Ratio		2.18%	1.35%	2.75%	2.01%	0.56%
Waste	Log Total Level	Landfill	3.33%	2.46%	3.00%	2.59%	0.60%
		Incineration	2.63%	2.00%	1.51%	1.55%	0.52%
	Intensity	Landfill	1.86%	0.88%	2.54%	2.56%	0.60%
		Incineration	1.46%	0.19%	2.28%	1.76%	0.52%
	Growth Rate	Landfill	0.67%	0.80%	1.45%	2.01%	–0.08%
		Incineration	0.29%	0.64%	–0.27%	0.58%	–0.18%
	Monetary Value	Landfill	3.14%	2.19%	3.40%	2.51%	0.52%
		Incineration	3.11%	1.72%	1.59%	1.21%	0.50%
	Impact Ratio	Landfill	1.90%	0.92%	3.10%	2.95%	0.59%
		Incineration	2.96%	1.97%	2.39%	2.84%	0.56%
Land & Water Pollutants	Monetary Value		2.60%	1.68%	1.41%	1.29%	0.50%
	Impact Ratio		1.10%	0.83%	2.38%	2.37%	0.56%
Air Pollutants	Monetary Value	Direct	3.36%	2.53%	3.11%	2.08%	0.47%
		Indirect	3.03%	1.88%	1.17%	1.33%	0.51%
	Impact Ratio	Direct	2.07%	1.93%	2.00%	1.79%	0.60%
		Indirect	3.11%	2.06%	3.16%	2.66%	0.56%
Natural Resource Use	Monetary Value		4.03%	2.39%	2.88%	1.89%	0.51%
	Impact Ratio		2.89%	2.23%	2.60%	1.99%	0.56%

(con in ed)

EXHIBIT 22 *(con in ed)*

Annualized Alphas of Long-Only Portfolios Constructed Using All Environmental Measures

			TB	EX	CO_{TB}	CO_{EX}	All
Panel B: Chinese Companies							
Carbon	Log Total Level	Scope 1	–2.64%	–2.64%	–5.42%	–5.42%	1.66%
		Scope 2	–1.76%	–1.76%	–1.53%	–1.53%	1.66%
		Scope 3	–1.89%	–1.89%	0.89%	0.89%	1.66%
	Intensity	Scope 1	–3.50%	–3.24%	–5.41%	–4.63%	1.66%
		Scope 2	–2.93%	–2.08%	–4.52%	–3.74%	1.66%
		Scope 3	–2.65%	–2.65%	–5.58%	–5.58%	1.66%
	Growth Rate	Scope 1	0.35%	1.06%	1.53%	1.94%	2.53%
		Scope 2	–1.04%	0.77%	–0.15%	1.76%	2.53%
		Scope 3	–0.30%	0.97%	1.90%	4.61%	2.53%
	Monetary Value	Direct	–2.68%	–2.68%	–6.41%	–6.41%	1.65%
		Indirect	–2.05%	–2.05%	0.40%	0.40%	1.66%
	Impact Ratio	Direct	–3.48%	–3.20%	–5.34%	–4.58%	1.67%
		Indirect	–3.47%	–3.47%	–4.99%	–4.99%	1.66%
Water	Log Total Level		–1.88%	–1.88%	–0.59%	–0.59%	1.66%
	Intensity		–3.47%	–2.72%	–3.02%	–1.99%	1.66%
	Growth Rate		–0.18%	0.64%	2.70%	3.95%	2.53%
	Monetary Value		–1.78%	–1.78%	1.47%	1.47%	1.65%
	Impact Ratio		–1.69%	–1.69%	–4.07%	–4.07%	1.66%
Waste	Log Total Level	Landfill	–0.52%	–0.34%	4.07%	1.66%	1.63%
		Incineration	–1.27%	–0.47%	0.92%	2.45%	1.93%
	Intensity	Landfill	–1.05%	–1.05%	–0.71%	–0.71%	1.63%
		Incineration	–0.60%	–0.98%	–1.85%	–0.56%	1.92%
	Growth Rate	Landfill	0.55%	1.36%	–0.89%	–0.69%	2.54%
		Incineration	0.05%	1.98%	–1.18%	–0.51%	2.57%
	Monetary Value	Landfill	–1.18%	–1.01%	0.69%	1.80%	1.62%
		Incineration	–2.08%	–2.08%	2.16%	2.16%	1.65%
	Impact Ratio	Landfill	–0.72%	–0.72%	–2.00%	–2.00%	1.64%
		Incineration	–3.81%	–3.98%	–5.33%	–5.44%	1.66%
Land & Water Pollutants	Monetary Value		–1.66%	–1.66%	–0.68%	–0.68%	1.65%
	Impact Ratio		–1.63%	–1.63%	–2.13%	–2.13%	1.66%
Air Pollutants	Monetary Value	Direct	–2.79%	–2.79%	–3.58%	–3.58%	1.66%
		Indirect	–2.30%	–2.30%	1.18%	1.18%	1.65%
	Impact Ratio	Direct	–4.79%	–2.23%	–3.61%	–3.80%	1.78%
		Indirect	–3.64%	–3.64%	–4.58%	–4.58%	1.66%
Natural	Monetary Value		–2.56%	–2.07%	0.40%	0.31%	1.65%
Resource Use	Impact Ratio		–5.69%	–3.10%	–5.13%	–1.75%	1.66%

markets.[30] Overall, we have documented a consistent negative correlation between measures of environmental greenness (e.g., negative values of carbon emissions) and residual returns, which leads to a cost (i.e., negative greeniums) in green investing based on these environmental measures in China. Unlike the US market, green investing in the Chinese market did not gain much attention until the of cial inclusion of carbon neutrality goals in China's "Fourteenth Five-Year Plan" in 2021. As a result, it is not surprising that the correlations are negative in our sample

[30] The corresponding results for long–short portfolios are provided in Appendix G of the online appendix. We also show the time-series correlations between the residual returns of portfolios constructed using different environmental measures in Appendix H of the online appendix. The residual returns are highly correlated, especially for long-only portfolios.

period. However, with carbon neutrality becoming a top-level national focus and concurrent rapid developments in green investing in China, it is reasonable to expect that these correlations may soon change, and the US market may offer valuable hints for the future.

CONCLUSION

In this article, we study the performance of impact portfolios constructed using a broad range of climate-related environmental measures, including carbon emissions, water consumption, waste disposal, land and water pollutants, air pollutants, and natural resource use, which are positively correlated with each other. In addition, impact factors constructed from these measures are generally positively correlated with the residual returns of stocks in the US market, implying positive excess returns (greeniums) over the past decade in the US market across all environmental measures we study.

To understand the difference between methodologies for constructing green portfolios, we compare the impact investing framework of Lo and Zhang (2021) based on Treynor–Black weights to several widely used green investing methodologies, such as exclusionary investing and impact-constrained portfolio optimization. We find that in the US market, Lo and Zhang's (2021) methodology outperforms other methods for both long-only and long–short portfolios in terms of both Fama–French five-factor alphas and information ratios. The same results hold for almost all other environmental metrics in our analysis, thus demonstrating the robustness of the Lo and Zhang (2021) methodology in practice.

The greeniums in the US market are closely related to the unexpected increase in climate concerns in our sample period. Using the MCCC index as a proxy, we find that an increase in climate concerns has an overall negative effect on the market and that the negative effect on green stocks is smaller than that on brown stocks, thus leading to positive excess returns for "green-minus-brown" portfolios. These results echo Ardia et al.'s (2022) and Pástor, Stambaugh, and Taylor's (2022) findings and suggest that the positive greenium over the past decade is (at least partially) due to an unexpected increase in climate concerns rather than reflecting ex ante expected returns.

Outside the United States, we also construct impact portfolios in the Chinese stock market. The average carbon emission, water consumption, and waste disposal levels for Chinese companies in our sample are generally higher than those for US companies. However, these metrics also decline more rapidly for Chinese companies than for US companies, which is consistent with the recent acceleration in carbon-neutrality efforts in China. In terms of portfolio performance, the greeniums for the Chinese market have been generally negative over the past decade, implying that impact investors have to bear a cost when holding low-carbon companies as opposed to high-carbon companies. These results are unsurprising, given that green investing in China did not gain much attention until recently. Our analysis of the US market may offer valuable insights about the future of green investing in China as it ramps up its carbon-neutrality efforts.

Our work provides a comprehensive analysis of investing based on a wide range of environmental measures for both the US and Chinese stock markets. We document the level of greeniums, analyze their sources, and demonstrate how impact investors can construct enhanced impact portfolios based on Lo and Zhang's (2021) framework. This may help impact investors achieve higher risk-adjusted returns, while maintaining the same level of social impact compared to simple exclusionary investing and traditional mean–variance optimized portfolios.

Our empirical results demonstrate that investing toward carbon neutrality does not always sacrifice risk-adjusted returns. The positive greeniums in the US market over the past decade may provide clues for where emerging markets are heading next. In the meantime, we also caution against interpreting ex post realized returns as the ex ante expected returns going forward, as demonstrated by the analysis of greeniums due to shocks in climate concern. Nonetheless, when investing toward carbon neutrality does create positive excess returns, one must understand where they came from and what risks are preventing investors from participating in these opportunities in the first place. Likewise, when these investments incur a cost to investors, this at the very least suggests the need for more explicit investor disclosures. It may also justify certain incentives and industrial policies, such as tax benefits and R&D grants to encourage the growth of low-carbon firms and organizations, to speed up our path to Destination Zero.

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