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Abstract

Does a green factor exist in the investment universe, one that would justify the development of offerings integrating a low carbon emission factor into the traditional factor menu? This is a question being raised, with increasing demand, by asset owners and asset managers. Certainly, in a context of climate urgency, there is a desire for a factor of this kind to exist and many researchers have tried to discover and to justify it. However, science is not always as responsive to social demand as some people might like.

Recent academic studies disagree on the effects that a firm's carbon emissions have on its stock performance. We argue that these studies do not in fact shed enough light on the issue to draw any conclusions. Whether "DeCarbonisation" is a factor that drives investment returns is a question that is worth asking but, in this note, we show that it has yet to be definitively answered.

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The UN Climate Change Conference COP 25 took place in Madrid in early December 2019, with delegates meeting to discuss the next steps needed to reduce global warming. In the past decade, firms' carbon emissions have come under stringent scrutiny, not just from local and international regulatory bodies but also by their essential stakeholders. Investors in general, and the asset management industry in particular, are putting much pressure on firms to reduce or at least control their level of emissions. A natural question is whether this pressure has led to any measurable market outcome. Unfortunately, there is no clear answer to this question.

In two recent papers, Cheema-Fox et al. (2019) and Bolton and Kacperczyk (2019) looked at the financial market implications of firms' carbon emissions. They reached quite opposite conclusions. The article by Cheema-Fox et al. (2019), which has been the subject of good marketing on the part of green solution providers, maintains that low carbon emission firms outperform high carbon emission ones. Bolton and Kacperczyk (2019), however, conclude that high carbon emissions have a positive impact on returns.

To shed light on this debate, we have tried to go a bit further than the public, and to our mind slightly too marketing-orientated, claims on the existence of a carbon factor that would be academicallyproven. With this in mind, we have analysed the two papers by Cheema-Fox et al. (2019) and Bolton and Kacperczyk (2019). Cheema-Fox et al. use carbon emissions data for US and European firms over a sample period spanning June 2009 to December 2018. They use data related to SCOPE 1 and 2 carbon emissions measuring direct and indirect emissions1. Sorting stocks according to their emission level, they look at the returns of a long-short portfolio which bets on the better performance of low emissions firms relative to high emissions firms. For US firms, annualised alpha after controlling for eight risk factors ranges from 0.25-3.01%, while the statistical significance, as measured by the t statistic, ranges from 0.27-1.96 (see Table 1). Conditional on positive flows from institutional investors, the alpha increases economically and its statistical significance improves (see Table 4).

Table 1: Regression on decarbonisation factor returns

Panel A: US

Variables	Select within i	t firms ndustry	Select within		Select within		Select in within		Select in within	dustries market	Select : within	
	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat	Estimates	t-stat
Alpha	0.25%	0.27	-0.95%	-0.76	1.89%	1.57	0.72%	0.51	2.52%	1.76	3.01%	1.96
Market	-0.03	-1.02	0.03	0.93	0.11	2.51	0.06	1.52	0.13	3.09	0.16	3.66
SMB	0.03	0.82	-0.06	-1.41	-0.15	-3.07	0.00	80.0	-0.15	-2.55	-0.18	-2.81
HML	0.03	0.64	-0.01	-0.20	0.30	4.86	0.07	1.15	0.14	1.84	0.11	1.37
RMW	0.06	1.11	-0.02	-0.34	-0.23	-3.35	-0.01	-0.17	-0.31	-4.30	-0.29	-3.42
CMA	-0.10	-2.11	-0.15	-2.39	-0.68	-6.41	-0.24	-2.55	-0.57	-4.32	-0.55	-3.81
WML	0.01	0.47	-0.02	-0.67	-0.01	-0.25	-0.06	-1.52	0.05	1.21	0.07	1.49
Oil	0.00	-0.09	0.03	1.45	-0.02	-1.05	0.04	3.22	-0.04	-2.15	-0.11	-5.39
Decarbonization Flows	0.39	2.17	0.81	3.87	0.49	1.77	1.05	2.34	0.55	1.10	1.06	1.64

This table presents estimates and t-statistics from non-overlapping monthly calendar regressions of decarbonisation factor returns on the eight factors tabulated, the five Fama-French factors (market, size, value, profitability, and investments), momentum, the NYMEX oil spot returns, and our defined decarbonisation flows. Alphas are annualised. This table originally appeared as Table 2 in Cheema-Fox et al. (2019).

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Bolton and Kacperczyk (2019) look at a sample of US companies over the period 2005 to 2017 to assess the impact of carbon emissions on market outcomes, i.e. the firms' monthly returns. They use the same emissions data as Cheema-Fox et al. (2019) augmented with SCOPE 3 emissions data. A robust finding is that higher carbon emissions have a positive impact on stock returns. This holds both for the level of emissions as well as the relative change (see Table 2). The emissions premium cannot be explained by standard risk factors such as the market, size and value premia (see Table 3).

Table 2: Carbon emissions and stock returns.

Panel A: Contemporaneous total emission	temporaneous total emission	poraneous to	Contem	Panel A:
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VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
LOG (TOT SCOPE 1)	0.060**			0.193***		
	(0.022)			(0.044)		
LOG (TOT SCOPE 2)		0.120**			0.199***	
		(0.044)			(0.057)	
LOG (TOT SCOPE 3)			0.172***			0.358***
			(0.049)			(0.084)
Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	190,548	190,476	190,644	190,548	190,476	190,644
R-squared	0.197	0.197	0.197	0.200	0.200	0.200

Panel B: Growth rate in total emission	าทร

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
DSCOPE 1	0.721***			0.725***		
	(0.211)			(0.195)		
DSCOPE 2		0.429**			0.424**	
		(0.181)			(0.179)	
DSCOPE 3			1.305***			1.329***
			(0.419)			(0.419)

•		

Year/month F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.	No	No	No	Yes	Yes	Yes
Observations	158,096	158,000	158,168	158,096	158,000	158,168
R-squared	0.212	0.212	0.212	0.215	0.215	0.215

The sample period is 2005-17. The dependent variable is RET. All variables are defined in the Appendix. We report the results of the pooled regression with standard errors clustered at the firm and year level. All regressions include year-month fixed effects. In columns (4) through (6), we additionally include industry-fixed effects. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon total emissions. ***1% significance; **5% significance; *10% significance. This table originally appeared as Table 6 of Bolton and Kacperczyk (2019).

Using 25 portfolios of stocks sorted on size and book-to-market, they investigate whether the carbon emissions anomaly is a pervasive risk factor. While the loadings of the 25 portfolios are economically sizable and statistically significant, the associated market price of carbon emissions risk is not significant (see Table 5). Overall, the evidence of an anomaly is strong but there is no evidence of a priced factor.

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Equity portfolios load significantly on the carbon factor, indicating that the return variability of these portfolios is influenced by this factor. Carbon exposure of equity portfolios is thus informative if investors want to understand drivers of variability of short-term portfolio returns. However, for investors who want to identify factors that drive differences in long-term return levels, a requirement is that a factor is priced. If a factor is not priced in the cross section of returns, it does not have an influence on long-term return levels. Tilting to such a factor, or away from it, will not have an influence on expected long-term returns and, conversely, will prevent one from benefitting from the true rewarded factors in the best conditions.

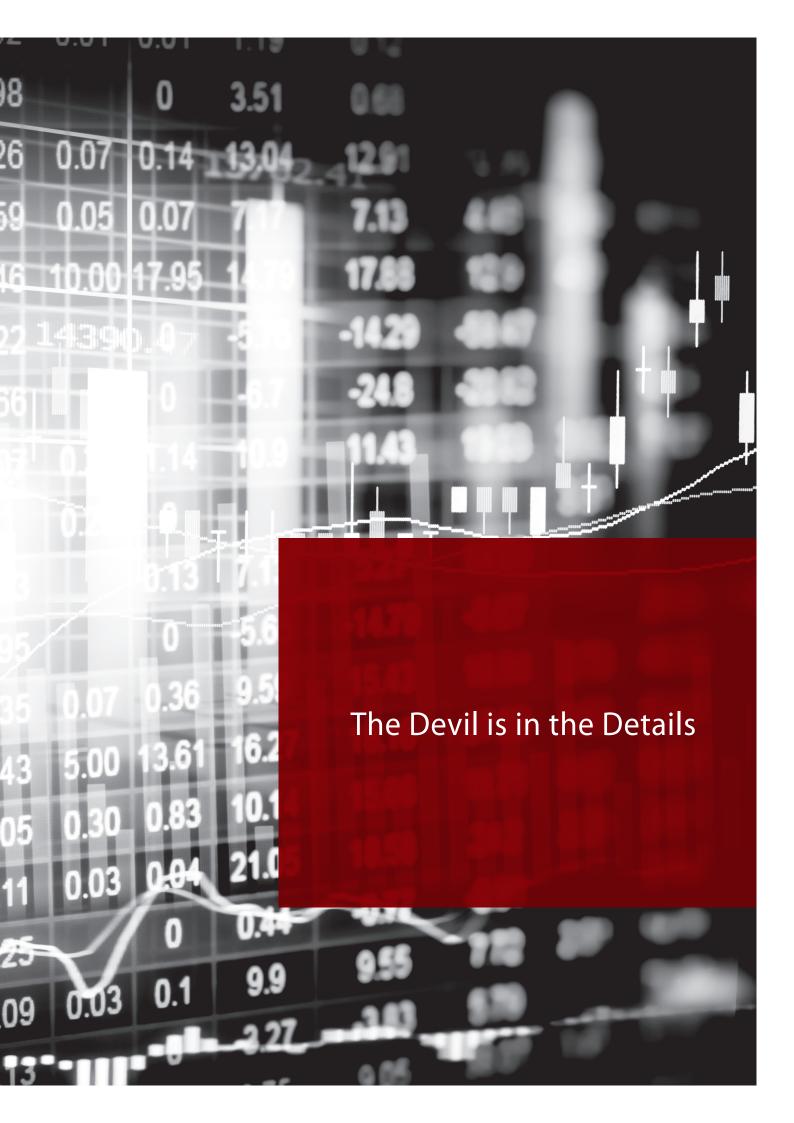
Table 3: Can the carbon promium be explained by rick factors?

	TOT SO	COPE 1	TOT SO	COPE 2	TOT SCOPE 3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MKTRF -		-1.528*		3.206***		3.124**
		(0.782)		(1.090)		(1.391)
•••						
Constant	0.068**	0.063**	0.095**	0.076***	0.120***	0.079***
	(0.027)	(0.025)	(0.037)	(0.029)	(0.036)	(0.028)
Industry adj.	No	No	No	No	No	No
Adj. R2	0.001	0.300	0.001	0.307	0.001	0.223
Observations	156	156	156	156	156	156

Panel B: Growth rate	in total emissions					
	DSC	OPE 1	DSCO	OPE 2	DSCOPE 3	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
MKTRF		3.317		-4.280		3.798
		(5.682)		(2.666)		(9.391)
	•					
Constant	0.642***	0.665***	0.446***	0.499***	1.500***	1.427***
	(0.095)	(0.130)	(0.068)	(0.068)	(0.238)	(0.247)
Industry adj.	No	No	No	No	No	No
Adj. R2	0.001	0.114	0.001	0.190	0.001	0.279
Observations	144	144	144	144	144	144

The sample period is 2005-17. The dependent variable is the monthly carbon premium estimated each period using a cross-sectional return regression. All variables are defined in the Appendix. We report the results of the time-series regression with standard errors adjusted for autocorrelation with 12 lags using Newey-West test. Panel A reports the results for the natural logarithm of contemporaneous total emissions; Panel B reports the results for the percentage change in carbon emissions. ***1% significance; **5% significance; *10% significance. This table originally appeared as Table 9 of Bolton and Kacperczyk (2019).

The evidence of a carbon emissions anomaly is very strong in Bolton and Kacperczyk (2019) but weaker in Cheema-Fox et al. (2019). Note that the latter provide no evidence as to whether carbon emission is a factor, while Bolton and Kacperczyk (2019) show that there is no such evidence in the data. Finally, the findings are contradictory: Cheema-Fox et al. (2019) hint at an outperformance of low emissions firms while Bolton and Kacperczyk (2019) indicate exactly the opposite, namely an outperformance of high emissions firms. This lack of statistical significance associated with contradictory economic results does not argue in favour of the existence of a carbon factor, as too many commentators have done, nor support its integration in the systematic long-term investment menu based on priced (i.e. rewarded) factors. Naturally, given the importance of the subject, we felt it was useful to do an in-depth analysis of the reasons for this conclusion, which are many.



The Devil is in the Details

ESG issues are of great significance in today's investment universe, especially when it comes to carbon emissions. Hence it is of prime importance to separate fact from fiction when it comes to the existence or absence – of a carbon factor. When papers come to conflicting conclusions, the contradictions most frequently stem from differences in data quality and/or empirical methodology. We investigate both of these inputs hereafter.

So is it the data?

For papers dealing with ESG and financial performance, we are used to contradictory findings and it is now well understood that mixed evidence frequently comes from the data. Berg, Kölbel and Rigobon (2019), Gibson et al. (2019) and Kotsantonis and Serafeim (2019) have all documented a low correlation amongst ESG data vendors and even pointed to a price impact stemming from this disagreement. More precisely, Berg, Kölbel and Rigobon (2019) relate the divergences in the ratings to the subjective approach to ESG of the data vendor as well as the weights put on the multiple ESG dimensions. Gibson et al. (2019) even build a disagreement measure for ESG ratings in the spirit of the classical analysts' disagreement and show that this disagreement strongly correlates stock returns.

That said, data issues are unlikely to be at the origin of the opposite findings from Cheema-Fox et al. (2019) and Bolton and Kacperczyk (2019). As a matter of fact, carbon emissions data are quite well defined (SCOPE 1 and 2 in particular). Busch et al. (2019) report correlation of more than 0.98 for SCOPE 1 and 2 across five carbon data vendors.

Or is it the methodology?

If data is not an issue, then it has probably to do with the methodology. In a devastating paper, Hou, Xue and Zhang (2019) highlighted the relevance of scientific methodology when documenting some empirical patterns. They looked at the multitude of Pricing Factors identified by academics and showed that some of them may not be that robust given the sorting methodology used to build them. In addition, it is also now clear that the method used to elicit their explanatory power for the cross section of stock returns is itself determinant (Feng, Giglio and Xiu, 2019).



Unpicking Cheema Fox et al. (2019)

Unpicking Cheema Fox et al. (2019)

In Cheema-Fox et al. (2019), the title is already misleading since they are trying to isolate a carbon anomaly, and not a factor at all. That a long-short portfolio has an alpha does not mean it is necessarily a priced factor. At best Cheema-Fox et al. (2019) showed that there is an alpha attached to carbon emission; no cross sectional evidence has been provided as to its pricing. The Authors use six ways of sorting stocks, and obtain very different findings across them, which is a symptom reminiscent of Hou, Xue and Zhang (2019) point. Most importantly, the multifactor model they use is not standard since they augment the Fama and French (2015) five-factor model with the momentum factor as well as oil and deCarbonisation flows.

The flow variable seems to drive most of the findings in this paper, in particular for Europe where it is significant in almost all regressions. Conditioning on positive flows, the findings are even more impressive according to the Authors, although they are not! For the US, for example, two alphas which are unconditionally barely significant (2.52% and 3.01%) are no longer significant when conditioning on flows! The other four, which were not, are significant when conditioning on positive flows.

Table 4: Decarbonisation factor performance conditional on flows

Region	Select firms within industry	Select firms within sector	Select firms within market	Select industries within sector	Select industries within market	Select sectors within market
US Alpha	2.03%	4.43%	3.29%	2.85%	1.48%	2.05%
t-stat	2.13	3.25	2.16	2.39	0.90	0.90
Europe Alpha	2.50%	2.62%	5.12%	4.16%	8.22%	8.51%
t-stat	2.15	2.06	2.90	3.25	3.71	3.73

This table presents estimates of alpha from calendar time regressions of a factor that goes long on the decarbonisation factor in months with positive decarbonisation flows and short on the decarbonisation factors in months with negative flows. Alphas are annualized. Regressions use non-overlapping monthly data from July 2009 through December 2018. The models controls for all other factors except for decarbonisation flows. This table originally appeared as Table 5 in Cheema-Fox et al. (2019).

But this significance does not reach the bar put forward by Harvey, Liu and Zhu (2016) to account for the multitude of factor discoveries. What about negative flows? Unfortunately, no evidence is provided for this case. But evidence is provided showing that contemporaneous flows matter, not lagged ones. This raises a suspicion that the relationship between flows and returns to portfolios are just mechanical: positive flows mean market buys, prices are likely to increase and hence a positive performance to the portfolio! Looking at the cumulative performance in the positive and negative flow case, one sees that the relation is almost deterministic and opposite. Nowhere are reported the standard measure of goodness of fit of the models (adj. R2). It would have been interesting to look at the marginal contribution of flows for explaining the returns to the long-short portfolio.

A preliminary evidence of the performance of the carbon long-short portfolio with usual factors would be useful for the reader to assess how reliable is the documented alpha. If any, this regression should speak to the Authors since it would have reduced the explanatory ability of traditional factors and hence increase even more the alpha of the portfolio. What about cross sectional performance? No evidence is provided and therefore we cannot conclude to a carbon factor.



Unpicking Bolton and Kacperczyk (2019)

The Bolton and Kacperczyk (2019) study follows a different route to identify a carbon emissions anomaly. Using panel data regressions, they show that returns are positively related to carbon emissions both in level and changes. To document an alpha attached to carbon emission, the Authors follow an original methodology, which has nothing to do with the standard Asset Pricing literature. Using a period by period Panel data regression, they obtain the coefficient on carbon emissions when the dependent variable is the monthly return. The time series of this coefficient is then regressed on a bunch of pricing factors and the constant from this multifactor regression is interpreted as an alpha. The findings are impressive! However, the size of the constant from these regressions is very different when using emissions or changes in emissions. It is not clear how this alpha should be interpreted.

In Bolton and Kacperczyk (2019), the carbon market price of risk is obtained from panel regression, where the Authors controlled for all the characteristics used to construct the factors from the time series. In the latter, they use the Fama and French size factor, but in the panel regression they already controlled for size. The same holds for value, investment and profitability factors. In principle, a significant coefficient from the panel regression on emission should be enough to conclude that carbon risk matters. Secondly, the coefficient on emission is interpreted as a market price of risk. It is well known that Fama-Macbeth coefficients from cross sectional regressions can be interpreted as premia on zero investment portfolios (Back, Kapadia and Ostdiek, 2015). Yet, it is very hard to guess how reasonable the portfolio positions are since no position constraint is accounted for. It would have been interesting to run the time series regression to isolate a carbon alpha by using the weights on the emissions variable to build a tradable portfolio. Instead, in the recent version of the paper, the Authors added a standard exercise where some portfolios are used to assess whether the loading on a carbon factor is priced. But the carbon emissions factor is a long-short portfolio unrelated to the implied portfolio from the cross sectional regressions. Moreover, test assets are the most problematic ones, ie the 25 portfolios sorted on size and book to market which are well known to have a very strong factor structure leading almost any factor to be significant in the cross section (Lewellen, Nagel and Shanken, 2010). Surprisingly, even in this extremely favourable research design, there does not seem to be room for a carbon factor!

Table 5: Is carbon premium systematic risk? Fama-MacBeth evidence

Cross-Section	SCOPE 1	SCOPE 2	SCOPE 3
Risk premium	0.531	0.470	0.351
t-statistic	1.07	1.34	0.89

The sample period is 2005-17. The table reports the results from estimating for each period the Fama-MacBeth regression of Fama-French assets on the carbon premiums. t-statistics are obtained using the autocorrelation-adjusted standard errors with 12 lags. This table originally appeared as Table 11 of Bolton and Kacperczyk (2019).



Conclusion: The Jury is Still Out

So is there a Carbon Anomaly?

Statistically, it is not clear from the findings of Cheema-Fox et al. (2019) and Bolton and Kacperczyk (2019) that there exists a carbon alpha. Even more worrying is the fact that the long-short portfolios in these studies are built in opposite ways. Hence, we are still not able to tell whether low emissions firms outperform high emission ones.

Is there a Carbon Factor?

Cheema-Fox et al. (2019) provide no answer to this question while Bolton and Kacperczyk (2019) conclude that such a factor does not seem to be relevant. All in all, no evidence so far supports the existence of a carbon factor.

So What Next?

First, besides conducting an investigation using standard methodologies, there is one important missing ingredient in these studies: time variation in alpha. Climate issues have been latent for a long time and only became central to the investment industry in the past decade. Assuming a constant alpha across the last 15 years is therefore not helpful, since even if an anomaly has appeared, it is likely that this happened in a progressive way, increasing over time. As clearly shown by Lioui (2018a and 2018b), both the alphas and risk premia attached to ESG are time varying. It is very likely that this is also the case for carbon emissions.

Secondly, while informative, such an exercise is useful only if supplemented with out-of-sample evidence. This is no guarantee of performance, but it at least helps in assessing the existence and size of any risk premium available to be harvested by a real time investor.

Finally, contrary to corporate governance and social matters, emissions are clearly related to environmental Corporate Social Responsibility and the real activity of the firm. Emissions are thus necessarily related to a firm's real characteristics. Therefore, for the exercise to be convincing, one has to run a horse race of carbon emissions with other firm characteristics – and show that the former do survive.

And Finally!

Taking all these matters into account, we are still in the dark as to the existence of any carbon anomaly or pricing factor. Establishing their existence – or the lack of it – is very important given the current debate on the financial cost of Corporate Social Responsibility, not only for firms but also for investors. Papers like Cheema-Fox et al. (2019) entertain the hope that there may be a bonus for doing good; this may be so, but we are very far from having convincing evidence!

Conclusion: The Jury is Still Out

Should this lack of evidence lead us to give up on doing good and, especially, to avoid divesting from firms that have a strong impact on global warming through their unacceptable levels of greenhouse gases?

Our answer here is unreservedly 'NO'. What is at stake with climate change goes beyond what is at stake with the existence or otherwise of a factor. Moreover, the fact that there is no carbon factor should lead us to conclude that while there is no positive risk premium to being low carbon, there is no negative risk premium either. In the current state of scientific knowledge, it is therefore possible, on the basis of traditional, consensus-based, rewarded factors, to construct portfolios that exclude the bad apples of the climate class without this posing a major problem for the performance or risk of these portfolios. Simply, this more modest approach, which does not make carbon a factor in performance, means that providers and investors should stop overselling green performance to their stakeholders. They should explain instead that there is no harm in doing good and that as far as the fight against climate change is concerned, this should not depend on hasty and fragile conclusions on the existence of a carbon factor.



Appendices

Appendix One: Anomaly vs Priced Factor

Traditionally, a pattern from the stock market is termed an anomaly when sensitivity to the market is not enough to explain this pattern. For example, one can sort stocks into deciles based on their market capitalisation. A typical pattern is that the lowest decile portfolio will earn an average return higher than the highest decile portfolio. The sensitivity of the portfolio returns to the market (their beta) cannot explain the spread in returns between the low and the high decile. This pattern is termed the size anomaly.

Whether the anomaly is a factor is the next step in the instigation. The idea is that the spread between the low and high decile must be driven by some differential exposure to a fundamental source of risk of the two portfolios. The question is: what is this source of risk? A short cut used by the profession is to take a portfolio long small stocks (low decile) and short big stocks (high decile) as a proxy for this fundamental source of risk. A factor is born! If the latter is pervasive, then it should appear in the cross section of the stock returns. To show it, one look at the sensitivity of stocks or portfolios to this factor and see if the loading on this factor helps align the cross sectional difference in returns across stocks and portfolios. If not, we are left with an anomaly but not a factor.

Appendix Two: Definitions of Emissions

Companies frequently use the standards defined by the Greenhouse Gas Protocol, a partnership between the World Business Council for Sustainable Development and World Resources Institute to provide global standards on emissions. These broadly break down emissions of greenhouse gases in into three "Scopes":

- SCOPE 1: Direct emissions, which include fuel combustion, company vehicles and fugitive (or unintended) emissions.
- SCOPE 2: Electricity indirect emissions, which comprise those from consumption of purchased electricity, heat or steam.
- SCOPE 3: Other indirect or value chain emissions, which encompass the likes of extraction and production of purchased materials and fuels or transport-related activities. These often represent the largest source of emissions, up to 90% of the total carbon impact.

Appendix Three: Variable definitions as per Tables from Bolton and Kacperczyk (2019)

Summary statistics (averages, medians, and standard deviations) for the variables used for the six sets of regressions. Originally from Table 1 of Bolton and Kacperczyk (2019).

- RET is the monthly stock return;
- LOGSIZE is the natural logarithm of market capitalization (in \$ million);
- B/M is the book value of equity divided by market value of equity;
- ROE is the return on equity;
- LEVERAGE is the book value of leverage defined as the book value of debt divided by the book value of assets;
- MOM is the cumulative stock return over the one-year period;

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- INVEST/A is the CAPEX divided by book value of assets;
- HHI is the Herfindahl index of the business segments of a company with weights proportional to revenues;
- LOGPPE is the natural logarithm of plant, property & equipment (in \$ million);
- BETA is the CAPM beta calculated over the one year period;
- VOLAT is the monthly stock return volatility calculated over the one year period.
- MKTRF is the monthly return on the value-weighted stock market net of the risk free rate;
- HML is the monthly return on the portfolio long value stocks and short growth stocks;
- SMB is the monthly return on the portfolio long small-cap stocks and short large-cap stocks;
- MOM (factor) is the monthly return on the portfolio long 12-month stock winners and short 12-month past losers;
- CMA is the monthly return of a portfolio that is long on conservative investment stocks and short on aggressive investment stocks;
- BAB is the monthly return of a portfolio that is long on low-beta stocks and short on high-beta stocks; LIQ is the liquidity factor of Pastor and Stambaugh;
- NET ISSUANCE is the monthly return of a portfolio that is long on high-net-issuance stocks and short on low-net-issuance stocks. Net issuance for year t is the change in the natural log of splitadjusted shares outstanding from the fiscal yearend in t-2 to the fiscal yearend in t-1;
- IDIO VOL is the monthly return of a portfolio that is long on low idiosyncratic volatility stocks and short on high idiosyncratic volatility stocks. Panel D reports the business-cycle variables. INF is inflation rate, measured as the consumer price index (CPI);
- TERM is the term spread measured as the difference between the 10-year and 1-year Treasury constant maturity rates;
- GDPGR is the quarterly GDP growth rate; GDP1YR is the growth rate a year later;
- DEFAULT is the default spread measured as the difference between BAA and AAA corporate bond rates. Panel E reports the unexpected profitability variable, calculated using the methodology in Vuolteenaho (2002).
- IOi,t is the fraction of the shares of company i held by institutions in the FactSet Database at the end of year t.
- IO is calculated by aggregating the shares held by all types of institutions at the end of the year, and then dividing this amount by shares outstanding at the end of the year.
- IO_BANKS is the ownership by banks;
- IO_INSURANCE is the ownership by insurance companies;
- IO_INVESTCOS is the ownership by investment companies (e.g., mutual funds);
- IO_ADVISERS is the ownership by independent investment advisers;
- IO_PENSIONS is the ownership by pension funds;
- IO_HFS is the ownership by hedge funds.



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About Scientific Beta

EDHEC-Risk Institute set up Scientific Beta in December 2012 as part of its policy of transferring know-how to the industry. Scientific Beta is an original initiative which aims to favour the adoption of the latest advances in "smart beta" design and implementation by the whole investment industry. Its academic origin provides the foundation for its strategy. offer, in the best economic conditions possible, the smart beta solutions that are most proven scientifically with full transparency of both the methods and the associated risks. Smart beta is an approach that deviates from the default solution for indexing or benchmarking of using market capitalisation as the sole criterion for weighting and constituent selection.

Scientific Beta considers that new forms of indices represent a major opportunity to put into practice the results of the considerable research efforts conducted over the last 30 years on portfolio construction. Although these new benchmarks may constitute better investment references than poorly-diversified cap-weighted indices, they nevertheless expose investors to new systematic and specific risk factors related to the portfolio construction model selected.

Consistent with a full control of the risks of investment in smart beta benchmarks, Scientific Beta not only provides exhaustive information on the construction methods of these new benchmarks but also enables investors to conduct the most advanced analyses of the risks of the indices in the best possible economic conditions.

Lastly, within the context of a Smart Beta 2.0 approach, Scientific Beta provides the opportunity for investors not only to measure the risks of smart beta indices, but also to choose and manage them. This new aspect in the construction of smart beta indices has led Scientific Beta to build the most extensive smart beta benchmarks platform available which currently provides access to a wide range of smart beta indices.

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About the EDHEC Scientific Beta Research Chair

The EDHEC Scientific Beta "Advanced Factor & ESG Investing" Research Chair was set up to transfer academic knowledge to the investment industry by providing high-quality research for decision-makers in the professional arena. The primary motivation for the research chair is to respond to real-world questions regarding factor investing with research that is recognised for its scientific quality.

The objectives of this chair are to contribute with research with strong academic potential to, and to be able to participate in, the development of knowledge on factor investing and ESG, which are two subjects of strategic importance for the investment industry.

Over the next three years, the EDHEC Scientific Beta "Advanced Factor & ESG Investing" Research Chair will address the following topics:

- Investability and factor crowding
- Questioning the ESG factor
- Factor premia regimes and the link between macro and micro factors
- Machine learning in factor investing
- How deep learning can improve the quality of ESG information
- Digital age, intangible investing and factor definitions
- New beta measurement methodology



About EDHEC Business School

Founded in 1906, EDHEC is now one of Europe's top 15 business schools . Based in Lille, Nice, Paris, London and Singapore, and counting over 90 nationalities on its campuses, EDHEC is a fully international school directly connected to the business world. With over 40,000 graduates in 120 countries, it trains committed managers capable of dealing with the challenges of a fast-evolving world. Harnessing its core values of excellence, innovation and entrepreneurial spirit, EDHEC has developed a strategic model founded on research of true practical use to society, businesses and students, and which is particularly evident in the work of EDHEC-Risk Institute and Scientific Beta. The School functions as a genuine labouratory of ideas and plays a pioneering role in the field of digital education via EDHEC Online, the first fully online degree-level training platform. These various components make EDHEC a centre of knowledge, experience and diversity, geared to preparing new generations of managers to excel in a world subject to transformational change.

EDHEC in figures: 8,600 students in academic education, 19 degree programmes ranging from bachelor to PhD level, 184 professors and researchers, 11 specialist research centres.

For more information: www.edhec.edu

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