THE JOURNAL OF
impact&esg
INVESTING

PORTFOLIO
MANAGEMENT
RESEARCH
By With Intelligence

volume 1
issue 1

JESG.pm-research.com

fall
2020

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KEY FINDINGS

- Environmental, social, and governance (ESG) signals are an important part of factor-based investing strategies, as they can stem from the same economic rationales as general factor premiums.
- Building portfolios by jointly optimizing factor exposures with ESG and carbon outcomes can result in similar historical performance as benchmark factor portfolios that do not include those considerations.
- Sustainable signals, which often involve alternative data, can be integrated in the definitions of factors themselves: We offer two examples on green intangible value and corporate culture quality that enhance traditional financial value and quality factors, respectively.

ABSTRACT: *Environmental, social, and governance (ESG) signals are an important part of factor-based investing strategies as they can stem from the same economic rationales as general factor premiums. Because factors are broad and diversified, building portfolios by jointly optimizing factor exposures with ESG and carbon outcomes can result in similar historical performance as benchmark factor portfolios that do not include those considerations. We show how sustainable signals, which often involve alternative data, can be integrated in the definitions of factors themselves: We offer two examples on green intangible value and corporate culture quality which enhance traditional financial value and quality factors, respectively.*

TOPICS: ***Analysis of individual factors/risk premia, factor-based models, ESG investing****

*All articles are now categorized by topics and subtopics. **View at PM-Research.com.**

We integrate environmental, social, and governance (ESG) data into factor-based investment strategies. We state upfront that this framework takes no view on whether ESG is a rewarded source of return in its own right: Authors like Edmans (2011) and Eccles et al. (2014) advocate the predictive relation between ESG and firm returns is positive, whereas Hong and Kacpercyzk (2009) and Cheng et al. (2013) document that the relation is negative. In contrast, a voluminous asset pricing literature shows that factors—broad and persistently rewarded sources of returns like value, quality, and momentum—have historically outperformed market cap benchmarks over decades (Fama and French 1993) and even over centuries (Goetzmann and Huang 2018).[1] Different to most of the papers

[1] See Ang (2014) for a summary on style factors.

in a growing ESG literature, we show how to build factor portfolios with ESG signals—and because they are based first and foremost on factors, we can lean on the large theoretical and empirical factor literature to make a case on building factor strategies embedding ESG data for strategic allocation.[2]

Factor premiums result from economic rationales: rewards for bearing risk, structural or market impediments, and investors' behavioral biases. Some aspects of the *E* of ESG fall into the second category involving regulation: whether a climate treaty is adopted, the imposition of a carbon tax, or potential legislation that may strand certain assets. The *S* of ESG may reflect behavioral biases of investors, employees, managers, or other market participants. Some *G* effects may be associated with increases or decreases in agency risk. But, because there is aggregate confusion and wide divergence of ESG ratings (see Berg et al. 2019), some ESG variables may not meet these economic rationales. If certain ESG data are linked to risk or behavioral theories that are consistent with factor premiums, they may be useful in constructing factor portfolios.

First, the broad nature of factors means that their effects are observed across thousands of securities; in large portfolios, idiosyncratic risk is diversified away, leaving exposure only to a few factors (see Ross 1976). Not surprisingly, these factors, which have, historically, significantly forecasted excess returns, may be correlated with other firm characteristics that may not be systematically related to returns, or some of these characteristics may have data limitations giving low power to statistically reject the null that they do not predict risk-adjusted returns. These conditions often apply to ESG data because of its sparse nature and lack of standardization.

Because ESG variables—which include carbon emissions as an *E* variable—are correlated with factors and the effects of factors are so broad, joint optimizations of ESG outcomes with factors can result in portfolios with virtually identical realized returns and risk compared to factor portfolios optimized without ESG constraints. Intuitively, the optimizations trade off some ESG tilts that are positive for some factors (positive ESG scores for quality, for example) with those that are negative for other factors (negative ESG scores for small size) in a way that jointly maximizes the opportunity sets of the factors within the specified ESG improvements. Our analysis is similar to, but extends optimizations of factors with ESG like Kulkarni et al. (2017), but with all five factors (value, quality, momentum, low volatility, and size) individually and combined, and we also integrate carbon reductions as well as ESG improvements.

Even without joint ESG and carbon optimizations, we show that a factor portfolio constructed from a global equity universe with five factors brings a 10% reduction in carbon emission intensity and has a modestly better ESG score than the market benchmark. The low volatility factor has a 6.6% better ESG profile, on average, than the market but the size factor has, on average, 5.9% lower ESG scores than the market. When we optimize such that ESG scores improve, the low volatility factor is impacted least and the value factor is impacted most. The former is due to higher volatility stocks generally having lower ESG scores, so excluding the lowest rated ESG stocks has little effect on a low-volatility-factor portfolio. Low-priced stocks include some companies with very low ESG scores and, thus, we cannot hold some companies with the most attractive value exposures when there is a significant ESG improvement.

The second way we incorporate ESG into factor strategies is to explicitly use ESG data in the factor definitions. Factors have historically been persistently rewarded over the long run, but the way we measure them may change over time. Indeed, at the time of the publication of the first, seminal treatise on systematic investing, Graham and Dodd (1934), accounting practices were not standardized. The metrics to capture richness versus cheapness (for the value factor), or high-quality versus low-quality companies (for the quality factor) have evolved over time. A large part of the literature, in fact, argues for the merits of one metric over another, while the underlying economic notions of value, quality, and other factors are stable.[3]

[2]Review summaries such as Clark et al. (2015) and Friede et al. (2015) aggregate the findings of over 200 and 2,200 studies, respectively, to examine the relationship between ESG and corporate performance.

[3]Value has moved from book value as a measure of intrinsic value from Graham and Dodd (1934) and used by modern authors like Fama and French (1993) and Lakonishok et al. (1994), to other authors suggesting using different measures: past earnings (Basu 1977), future earnings (Dechow and Sloan 1997; Frankel and Lee 1998), cash flow (Fama and French 1996; Lettau and Wachter 2007), return on equity (Haugen and Baker 1996), and combinations of these and other variables (Piotroski 2000).

We use ESG data to evolve measures of factors beyond traditional balance sheet and earnings statement variables and treat ESG as a non-traditional data source to capture aspects of factors. We give two examples of non-financial value and quality. First, we measure a firm's output of innovation using green patent data—explicitly capturing long-term investment opportunities addressing climate change and other societal challenges. We extend quality beyond traditional financial quality, like accruals (Sloan 1996) and profitability (Novy-Marx 2013), to the quality of corporate culture using machine learning of textual data. Corporate culture reflects aspects of *S* and *G* of a firm such as human capital, innovation, and customer satisfaction, as well as corporate management.

FACTORS AND ESG DATA

We describe how we construct standard benchmark factor portfolios in the next section, Factor Data, and summarize the ESG scores and carbon data in the following section.

Factor Data

We build theoretical factor portfolios of five factor strategies—value, momentum, quality, size, and low volatility—in the MSCI World equity universe. Fundamental data from Worldscope and IBES are used to generate the momentum, value, quality, and size factors. For low volatility as well as momentum, we use equity returns and volatilities sourced from the MSCI Barra Global Equity Model (GEM3). We optimize the portfolios with MSCI GEM3 as the risk model. The simulation runs from December 1997 to September 2019 and rebalances monthly. The portfolios are constrained in terms of region, industry, and country to ensure risk is taken along the factor exposure dimension. In addition, we incorporate hypothetical transaction costs, with a similar model to Ratcliffe et al. (2017), and control for turnover.

We deliberately use standard factor definitions that are in the literature for baseline comparisons:

- **Value:** The value factor strategy combines three signals. The first two are forward-looking valuation metrics, using analysts' 12-months earnings forecasts with one divided by price and the other divided by enterprise value. The other valuation metric is a backward-looking measure: comparing a firm's cash flow from operations to its market capitalization.
- **Momentum:** The momentum factor strategy combines two signals: price trend over the past 12 months (excluding the most recent one month to control for reversal effects as per Jegadeesh and Titman 1993), and changes (up or down) in analysts' 12-month earnings forecasts.
- **Quality:** In the quality factor strategy, we combine four signals: gross profitability, free cash flow to debt, an accruals measure, and capex growth.
- **Size:** The size factor strategy uses the inverse of log of market capitalization.
- **Low volatility:** For the low volatility factor strategy, we use the inverse of idiosyncratic volatility following Ang et al. (2006), who show that there are larger return differences using idiosyncratic volatility vs. total volatility.

Finally, we build a combined theoretical multi-factor portfolio that blends the single factor metrics with a bottom-up basis (see Grinold and Kahn 2000). In this case, we first combine separate signals within each of the aforementioned five factors, and then compute a composite signal score for each individual stock equally combining the five factors.

Exhibit 1 reports summary statistics (Panel A) and a graph of cumulated returns (Panel B) of the factors from December 1997 to September 2019. All factors generate a positive information ratio over the sample period with momentum and quality having the highest active returns (portfolio return minus market benchmark) at 1.7% and 1.5% annualized, respectively.

Although the information ratios are positive over the sample, there has been substantial cyclicality for the factors, as Panel B of Exhibit 1 shows (see also Hodges et al. 2017). For example, the value factor's highest returns are from the beginning of the sample to the end of 2006, with an information ratio (IR) of 0.9. From January 2007 to September 2019, value has, on average, underperformed the market with an IR of −0.36 giving an IR of 0.12 over the full sample. Most recently, since the beginning of 2017 to the end of the sample, quality, momentum, and low volatility have outperformed, and size and value have underperformed the market.

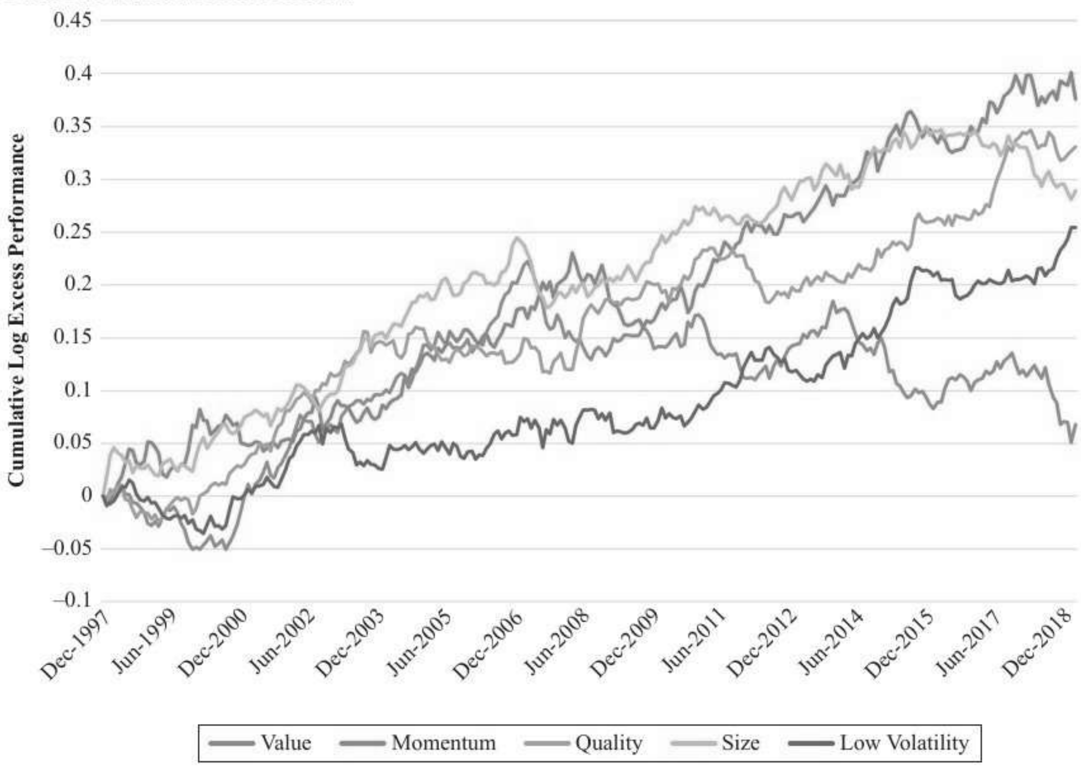
Exhibit 1

Summary Statistics of Benchmark Factor Portfolios (without ESG)

Panel A: Summary Statistics

Strategy	Information Ratio (IR)	Annualized Active Return	Annualized Active Risk
Value factor	0.12	0.30%	2.60%
Momentum factor	0.61	1.70%	2.80%
Quality factor	0.67	1.50%	2.30%
Size factor	0.59	1.30%	2.20%
Low volatility factor	0.62	1.40%	2.30%

Panel B: Cumulative Active Returns



Notes: Data from Worldscope, IBES, and Barra, period of returns shown: January 1998–September 2019. Past performance does not guarantee future results.

ESG and Carbon Data

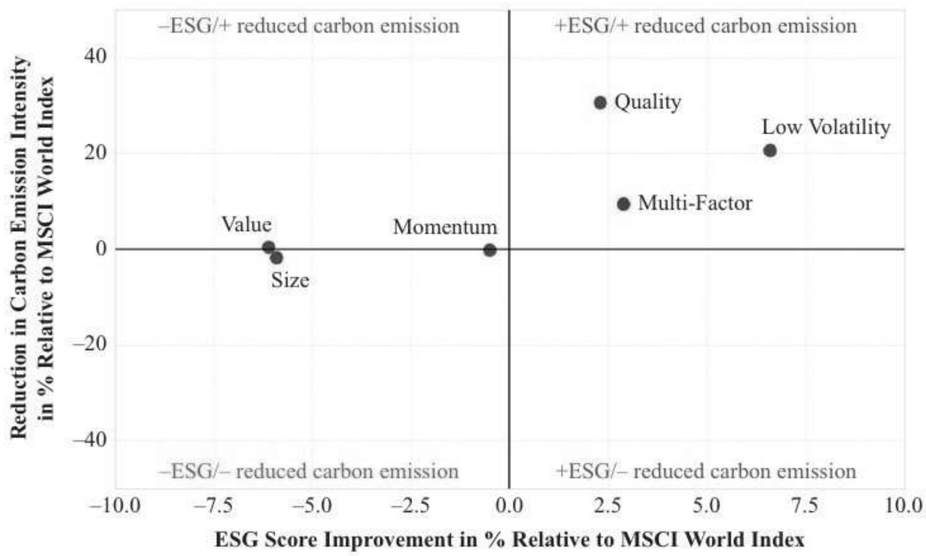
We define the ESG score as the MSCI ESG industry-adjusted score. MSCI ESG Ratings aim to measure a company's resilience to long-term, financially relevant ESG risks (see MSCI ESG Research 2019). We use the industry-adjusted ESG scores to form industry ESG-relative peer views, also consistent with industry controls in constructing our factors.

The paucity of ESG data is well noted by many authors, but coverage has increased over time.[4] Due to data availability, our ESG analysis uses data from 2015 onwards. In this period, almost 99% of the stocks in the MSCI World universe are covered. (For comparison,

[4] A good summary of the history of ESG ratings, as well as a broader industrial organization and "social construction" view of this data is provided by Eccles and Stroehle (2018). In the third section, ESG in Factors, we detail other proprietary ESG data which we deem suitable to incorporate in the definitions of the factors.

EXHIBIT 2

ESG Score and Carbon Emission Intensity of Benchmark Factor Portfolios



Notes: Data from Worldscope, IBES, MSCI ESG, and Barra, simulation period: January 2015–September 2019. Past performance does not guarantee future results.

in 2004 only 63% of stocks carried ESG ratings, and in 2009 only 81% of stocks were covered.)

Our carbon emission intensity is defined as Scope 1 and Scope 2 carbon emission divided by sales. We use the MSCI database, which collates company-specific direct (Scope 1) and indirect (Scope 2) greenhouse gas (GHG) emissions data from company public documents and the Carbon Disclosure Project (CDP).[5] At the company level, the carbon intensity is defined as (Scope 1 + 2 emissions in tons/$M sales in USD), which allows for comparison between companies of different sizes.

[5]Scope 1 emissions are those from sources owned by the company via company facilities or company vehicles, such as fleet vehicles or fuel combustion on site. Scope 2 emissions are those caused by the generation of electricity purchased by the company. Scope 1 and Scope 2 need to be reported by companies as a minimum for GHG accounting for reporting purposes like the Kyoto protocol. Carbon emission intensity also plays an important role as ESG regulations become effective in the near future, such as carbon taxes or initiatives such as the Portfolio Decarbonization Coalition (see https://unepfi.org/pdc/). Even though Scope 3 emissions tend to dominate, we do not use as these must be estimated by an input–output model and, therefore, tend to be dissimilar across data sources. We follow MSCI data in using Scope 1 and 2 emission data.

ESG AND CARBON PROFILES OF FACTORS

This section investigates the ESG and carbon statistics of the factors. The section ESG and Carbon Characteristics of Factors documents how the factors fare along ESG and carbon intensity dimensions relative to the market—with certain factors like quality and low volatility having significantly better ESG scores and carbon reductions. The second section analyzes how factor efficacy compared to sensitivity for ESG and carbon constraints. The traditional factor portfolios are already ESG-friendly, and there is even more scope to trade off the ESG considerations with factor performance, which we explore in the third and fourth sections.

ESG and Carbon Characteristics of Factors

Exhibit 2 summarizes the ESG and carbon scores of the benchmark factors relative to the MSCI World market portfolio over January 2015 to September 2019. The origin represents the market portfolio, so the ESG scores represent percentage *improvements* relative to the market on the x-axis and we plot percentage carbon emission intensity *reductions* on the y-axis. Thus, those factors in the top right-hand quadrant represent factors that have improved ESG scores and lower carbon emission intensities than the market as represented by the MSCI World Index.

Even without taking into account ESG considerations, Exhibit 2 shows that some style factor portfolios exhibit already a pro-sustainability profile: Quality and low-volatility portfolios are both higher in ESG ratings, at 2.3% and 6.6% relative to the market, respectively. Quality and low-volatility portfolios also have lower carbon emission intensities than the market, at 30.6 and 20.6%, respectively. These results are not due to sector or country biases of the factors as we impose country and industry constraints in constructing the factors. The significantly positive ESG profile of quality has been noted by several authors, including Northern Trust (2014) and Melas et al. (2016). Dunn et al. (2018) describe that ESG has important risk contributions, which are potentially captured directly in the low volatility factor.

The size and value factors are anti-ESG with 5.9% and 6.1% lower ESG ratings than the market, respectively. Part of the lower ESG score for smaller companies may be due to smaller companies publishing less pertinent ESG information than larger companies. Looking within the individual *E*, *S*, and *G* components, the lower ESG score for the value factor is primarily due to the *S* and *G* scores. The value factor, but not the size factor, has a lower carbon profile than the market—contrary to some opinions that value companies use older, carbon-intensive technologies. Finally, the momentum factor has approximately the same ESG and carbon profile as the market benchmark. Part of this may be due to momentum being one of the largest factors present in the market portfolio itself (see Madhavan et al. 2018).

Finally, the theoretical multifactor portfolio, shown in red in Exhibit 2, exhibits an 2.9% improvement in ESG and 9.4% lower carbon intensity relative to the market. Thus, investing in factors even without ESG considerations already produces a portfolio with above-average ESG and carbon characteristics.

Factor Sensitivity Versus ESG and Carbon Sensitivity

We now explore the effect of imposing ESG or carbon constraints on the long-only factor portfolios. Our procedure is as follows. So far, the factors are constructed using mean-variance optimization with the signals in the earlier section as expected returns, a risk model for the covariance, and various constraints to ensure there are no region or industry exposures away from the MSCI World Index, and we limit turnover. To this optimization, we add constraints that specify that the ESG or carbon profiles must be improved by a certain level (see Appendix).

Exhibit 3 graphs the effects on the factor exposures resulting from improving the ESG scores (Panel A) and carbon emission intensities (Panel B) relative to the market. We show the percentage difference in active factor exposure between the optimal portfolio with ESG/carbon constraints and the optimum without constraints. This gives us an indication of how much the additional constraint moves us away from the optimal factor exposure. For example, we compute the value portfolio without ESG or carbon constraints as per the unconstrained factors in Exhibit 1. At each point in time, this benchmark factor portfolio has a value exposure, formally given in terms of z-scores using the valuation metrics detailed in the earlier section, Factor Data. When we include ESG or carbon intensity constraints, the optimization produces a new value factor with lower value exposures. We show the average value factor exposure of the constrained ESG or carbon portfolio as a percentage of the factor exposure of the unconstrained factor over the sample, from January 2015 to September 2019.

Exhibit 3 represents different percentage improvements in ESG scores or carbon intensity ranging from at least at benchmark levels (0%) to up to 50% better in ESG scores (Panel A) or up to 80% better than benchmark in carbon intensity (Panel B). As Exhibit 2 makes clear, certain factors (especially quality and low volatility) already have better-than-average ESG or carbon profiles than the market without any constraints, as ESG or carbon improvements become tighter, the factor exposures decrease—which is as expected as when more and more stocks are removed from a portfolio, the more constrained space of the optimization can result in inferior factor exposure.

Panel A, Exhibit 3 shows that the low-volatility portfolio is the least affected by the additional ESG constraint and exhibits the least change in factor exposure. At the 20% ESG improvement level relative to the market, the low-volatility exposure decreases by 1.2%, and at

EXHIBIT 3

Factor Efficacy as ESG and Carbon Outcomes Improve

Panel A: ESG Score Improvement Relative to MSCI World Index

ESG Improvement		Value	Momentum	Quality	Size	Low Volatility
0%	ESG improvement	0.11%	1.07%	4.17%	0.86%	7.53%
	Exposure change	0.00%	0.00%	0.00%	0.00%	0.00%
10%	ESG improvement	10.00%	10.00%	10.19%	10.01%	10.83%
	Exposure change	–1.23%	–0.57%	–0.81%	–1.30%	–0.19%
20%	ESG improvement	20.00%	20.00%	20.00%	20.00%	20.00%
	Exposure change	–4.08%	–2.41%	–3.02%	–3.75%	–1.15%
30%	ESG improvement	30.00%	30.00%	30.00%	30.00%	30.00%
	Exposure change	–8.60%	–5.94%	–7.50%	–7.60%	–3.35%
40%	ESG improvement	40.00%	40.00%	40.00%	40.00%	40.00%
	Exposure change	–15.44%	–11.81%	–14.60%	–13.22%	–7.92%
50%	ESG improvement	50.00%	50.00%	50.00%	50.00%	50.00%
	Exposure change	–25.98%	–21.96%	–26.94%	–21.66%	–15.89%

Panel B: Carbon Emission Intensity Reduction Relative to MSCI World Index

Carbon Reduction		Value	Momentum	Quality	Size	Low Volatility
0%	Carbon reduction	14.28%	9.29%	30.48%	6.27%	24.37%
	Exposure change	0.00%	0.00%	0.00%	0.00%	0.00%
10%	Carbon reduction	17.53%	16.70%	31.94%	13.14%	24.98%
	Exposure change	–0.01%	0.00%	0.00%	–0.01%	0.00%
20%	Carbon reduction	22.83%	24.35%	34.20%	21.55%	27.44%
	Exposure change	–0.01%	–0.01%	–0.05%	–0.02%	–0.01%
30%	Carbon reduction	30.71%	32.14%	38.34%	30.62%	34.18%
	Exposure change	–0.05%	–0.06%	–0.12%	–0.04%	–0.06%
40%	Carbon reduction	40.08%	40.52%	43.92%	40.28%	42.38%
	Exposure change	–0.14%	–0.11%	–0.31%	–0.07%	–0.17%
50%	Carbon reduction	50.03%	50.08%	51.06%	50.10%	51.16%
	Exposure change	–0.33%	–0.22%	–0.66%	–0.11%	–0.45%
60%	Carbon reduction	60.00%	60.01%	60.02%	60.04%	60.23%
	Exposure change	–0.70%	–0.46%	–1.09%	–0.22%	–0.87%
70%	Carbon reduction	70.00%	70.00%	70.00%	70.00%	70.00%
	Exposure change	–1.53%	–1.02%	–1.79%	–0.48%	–1.71%
80%	Carbon reduction	80.00%	80.00%	80.00%	80.00%	80.00%
	Exposure change	–3.56%	–2.37%	–3.39%	–1.28%	–3.74%

Notes: Data from Worldscope, IBES, MSCI ESG, and Barra, simulation period: January 2015–September 2019. Past performance does not guarantee future results.

the 50% improvement level, the exposure decreases by 15.9%. Some of this is due to a size interaction because larger stocks have tended to be less volatile (see Ang et al. 2006), and larger stocks are also more likely to furnish ESG data. But not all. If we exclude the top 10% largest stocks by market capitalization, the exposures decrease to 1.5% and 20.7% at the 20% and 50% ESG improvement levels, respectively.

The value and quality portfolios are the most affected as ESG profiles improve. For the value factor, the decreases in factor exposure are 4.1% and 26% at the 20% and 50% ESG improvement levels, respectively. The decrease for the quality factor exposures are 3% and 27%, respectively. None of the factor portfolios, however, sees a meaningful change in factor exposure to achieve a 20–30% higher ESG portfolio than the market benchmark.

We perform a similar analysis in Exhibit 3, Panel B but now add an explicit carbon emission intensity improvement relative to benchmark. Carbon emission intensity is far from normally distributed and it is feasible to achieve a strong improvement in carbon emission intensities with minimal changes to the portfolio's factor exposures. The size factor exhibits the smallest decrease in factor exposures. Reducing carbon emission intensities by 50% results in a reduction in small size exposure of only 0.11%! But all the factors exhibit small decreases: The factor with the largest decrease in factor exposure is quality at the 50% carbon reduction level, which decreases its exposure by 0.66%. Again, none of the factor portfolios see a meaningful change in factor exposure when the aim is to achieve a 40%–60% lower carbon emission intensity portfolio than the benchmark.

What is driving these results is that there are a few, often very large, companies that account for the bulk of carbon emission intensities. Certainly a few industries and sectors account for outsized carbon emission intensities—but this is true also within the industries and sectors. Carbon emission intensities tend to be driven by three sectors: utilities, materials, and energy. Within materials, the metals and mining industry has the highest carbon emission intensities; within utilities, companies within power and renewable electricity producers are the largest emitters. Even companies within the same industry can have very different carbon intensity values.

Jointly Optimizing Factors, ESG, and Carbon Outcomes

We now construct optimized factor portfolios with simultaneous ESG and carbon intensity outcomes, using the same region, industry, and country constraints as the benchmark factor portfolios. We impose an *ex-ante* 20% improvement in ESG ratings and a 40% reduction in carbon intensities for each individual factor—value, quality, momentum, size, and low volatility—and the multifactor version containing all five factors.

Exhibit 4 reports *ex-post* ESG and carbon scores of the factor portfolios, together with performance statistics over January 2015 to September 2019. We have two tables, one for the benchmark factor portfolio without the additional ESG and carbon improvements and the other for the jointly optimized factors with ESG and carbon intensity improvements. The first column reports

EXHIBIT 4

Statistics with and without ESG and Carbon Improvements

	ESG Score	Carbon Emission Intensity	Exposure	Information Ratio (IR)
No ESG/Carbon Constraints				
Value	5.22	196.22	0.33	–0.22
Momentum	5.62	177.64	0.42	0.51
Quality	5.79	135.35	0.14	0.78
Size	5.60	177.75	0.94	0.45
Low volatility	5.68	180.56	0.44	0.52
Multifactor	5.72	178.46	0.27	0.65
With ESG/Carbon Constraints				
Value	6.67	117.70	0.31	–0.09
Momentum	6.67	116.49	0.40	0.57
Quality	6.67	108.21	0.13	0.77
Size	6.67	113.06	0.89	0.43
Low volatility	6.67	117.50	0.43	0.53
Multifactor	6.67	117.20	0.27	0.77

Notes: Data from Worldscope, IBES, MSCI ESG, and Barra, simulation period: January 2015–September 2019. Past performance does not guarantee future results.

ESG scores, showing the ESG/carbon optimized factor achieves ESG scores in excess of 6.6, compared to the benchmark factor scores around 5.6 to 5.8. In particular, the benchmark multifactor portfolio has an ESG score of 5.7 versus the market of 5.3. (Note the multifactor portfolio already improves upon the ESG profile of the market as Exhibit 2 shows.)

The second column of Exhibit 4 plots carbon intensities. To interpret the units, recall the carbon intensity is defined as (Scope 1 + 2 Total Emissions tonnes CO2/ $M Sales). The ESG/carbon optimized factor portfolios can further improve their carbon efficiency from 166 tn/$ to 115 tn/$ on average. Momentum, size, and low volatility see the largest improvements, while quality has the lowest—but the improvement for quality is still reduces emission intensities from 135 tn/$ to 108 tn/$.

The third column of Exhibit 4 reports the factor exposures given in terms of z-scores for the benchmark factor portfolios and the factor portfolios with ESG/carbon improvements. This is similar to Exhibit 3, which plots a ratio of the factor exposures, but Exhibit 4 displays the factor exposures for the specific ex-ante targets of 20% ESG improvement and 40% carbon emission intensity reduction. On average, by jointly optimizing ESG scores and carbon emission intensity, the factor portfolios' active exposures reduce only by approximately 3%. Low volatility sees a very muted exposure change of only −0.7%.

Finally, the last column of Exhibit 4 shows the in-sample performance of the raw factors compared to the optimized ESG/carbon factors. We acknowledge that our sample, over January 2015 to September 2019, is short, but it is notable how similar the IRs are for both portfolios. For example, the sample period is not kind to the value factor portfolio, which has an IR of −0.23 without ESG/carbon improvements and −0.09 optimizing with ESG and carbon. For the multifactor portfolio, the IRs are 0.66 and 0.78, respectively. The ex-post tracking errors between the factor portfolios with and without ESG improvements range from 0.60% for the momentum factor portfolio to 0.96% for the size factor portfolio. Of course, we expect that ex ante, any additional constraint will cause the objective function to be weakly lower, so these apparent improvements are likely attributable to sampling error—the important point is the ex-post performance is very similar constructing factor portfolios with and without ESG and carbon improvements.

Overall, these results suggest the marginal cost of trading one stock over another based on only style factor exposures is relatively low, while the marginal benefit to ESG improvement is high. This is a fundamental characteristic of factor portfolios that makes them a potentially effective way of achieving ESG goals with limited impact on investment performance.

Comparing the Jointly Optimized Factor, ESG, and Carbon Portfolio

Exhibit 5 compares the joint optimized multifactor portfolio with the 20% ESG improvement and 40% carbon reduction (multifactor portfolio with ESG/carbon improvements) with portfolios optimizing only ESG and carbon emission intensities. We construct two versions of the latter: using the ESG score as an alpha input to our optimization (Max ESG) and using the carbon intensity as an alpha input (Min Carbon).

Panel A plots the ESG improvement (x-axis) and the reduction in carbon emission intensities (y-axis) for the three aforementioned portfolios, together with some comparable ESG strategies. First, the orange dot is the multifactor portfolio constructed with the 20% ESG improvement and the 40% reduction in carbon. This is comparable to the MSCI World ESG Screened Index, which achieves an almost 40% reduction in carbon with a minimal ESG improvement, and the MSCI World SRI Index, which has a 60% reduction in carbon emission intensities with a 30% improvement in ESG ratings. These two indices are market-cap weighted indices on an ESG screened universe and are, therefore, less diversified portfolios. The MSCI World ESG Enhanced Focus Index aims to maximize the overall ESG score with a 30% improvement in carbon intensity relative to benchmark and sees an ESG improvement of 20%.

The Min Carbon portfolio exhibits a very large reduction of carbon emission intensity of over 90% along with a small ESG improvement. The very high reduction in carbon emission intensity is due to the distribution of the carbon emission intensity, which we also encountered in the section Factors & ESG Data. The Max ESG obtains a 40% improvement in ESG with a 20% reduction in carbon, but although the sustainability profile is better than the multifactor portfolio with ESG/carbon improvements, the factor exposures are unsatisfactory. The Min Carbon portfolio has, with the exception of a size tilt, no other factor exposures as shown in Panel B of Exhibit 5.

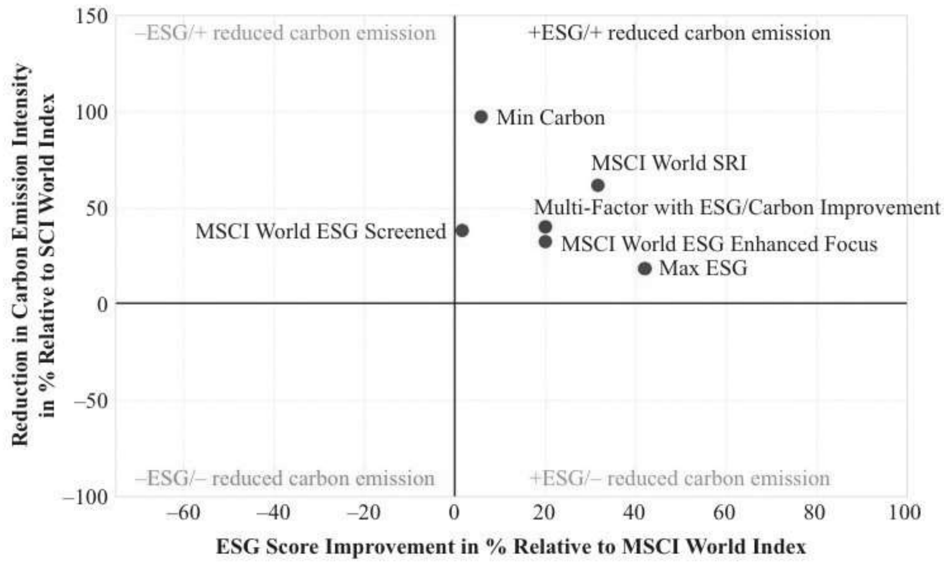
The Max ESG portfolio, however, has some interesting factor loadings: The positive momentum and negative value exposure suggest that good ESG companies have seen trending prices in the recent past. The mildly positive exposure to quality reconfirms there is a correlation between ESG scores and a company's quality characteristics. Notwithstanding the negative correlation of −20% between ESG scores and size factor exposures, the Max ESG portfolio results in a large size exposure alongside a high volatility exposure. This is counterintuitive but shows how constructing a long-only factor portfolio with only one variable can result in unintended biases.[6] In contrast, the multifactor portfolio with ESG/carbon improvements has a much more

[6] Within the portfolio optimization we have a maximum asset weight constraint, which the optimizer tries to utilize as much as possible by selecting the few companies with an ESG score of, or close to, 10. If we modify the upper asset weight constraint to be the minimum of 2% and four times the benchmark weight, the size exposure reduces significantly; the other factor exposures remain similar and the IR increases but at the expense of the portfolio level ESG score.

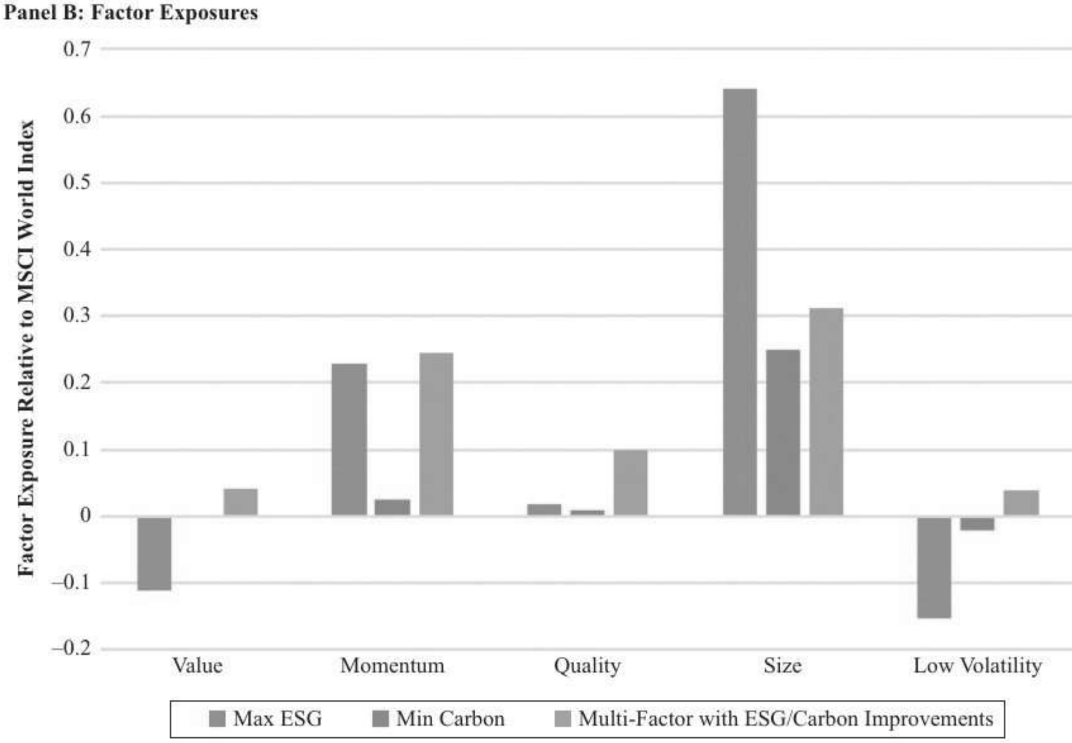
EXHIBIT 5

Comparing Optimized ESG/Carbon Factor Portfolios

Panel A: ESG Scores and Carbon Emission Intensities



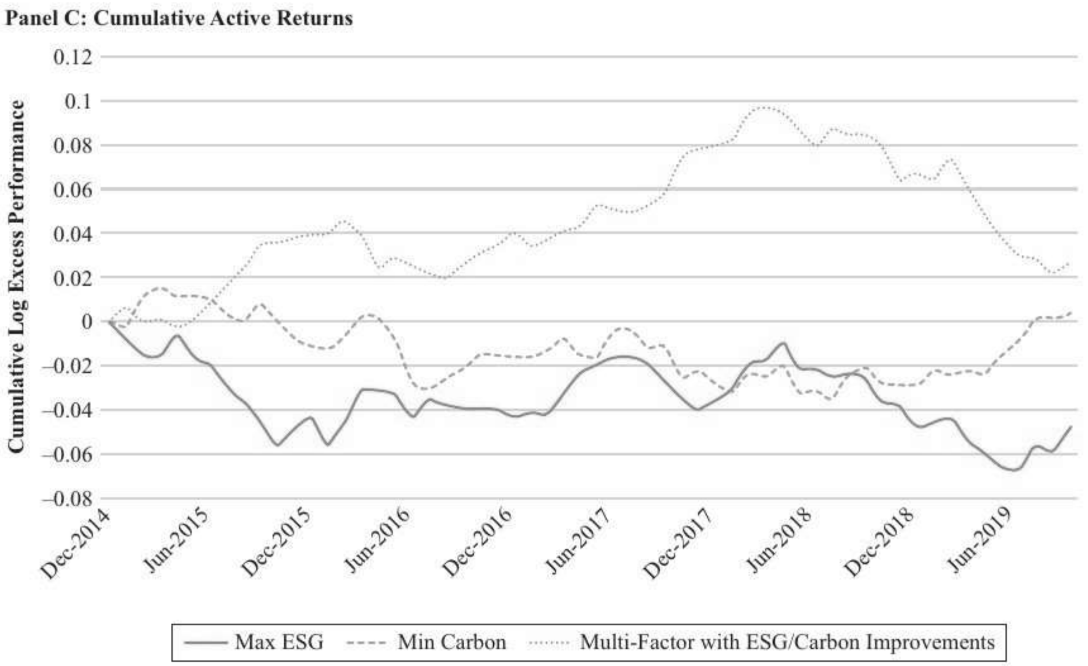
Panel B: Factor Exposures



(continued)

EXHIBIT 5 *(continued)*

Comparing Optimized ESG/Carbon Factor Portfolios



Notes: Data from Worldscope, IBES, MSCI ESG, and Barra simulation period: January 2015–September 2019. Past performance does not guarantee future results.

balanced exposure to targeted style factors, which are a rewarded source of return. In Exhibit 5, Panel C, this results in a positive IR of 0.23 from 2015 to September 2019; the Min Carbon and Max ESG portfolios have IRs of 0.03 and −0.41, respectively.

ESG IN FACTORS

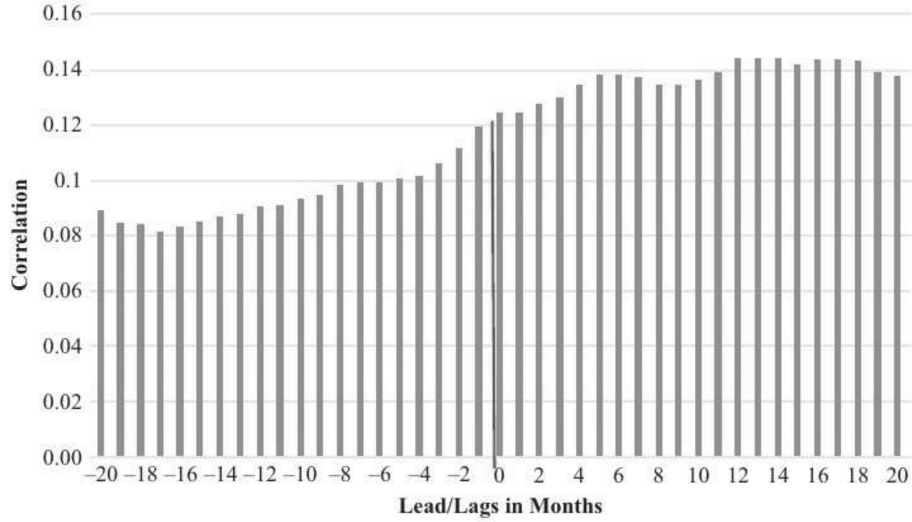
Although the previous section shows how to take advantage of the correlation between ESG ratings, carbon scores, and factor exposures to construct factor portfolios that jointly optimize all three—we have, so far, taken the sustainability data to be exogenous. In this section, we give two examples of how innovative ESG data can be incorporated in the factor definitions themselves. The first section, "Green Intangible Value," shows how to use ESG data in a value factor by using green patent information. The second section, "Corporate Culture Quality," describes how to incorporate corporate culture into a quality factor. Incorporating nontraditional ESG data to capture salient aspects of factors, but not relying solely on ESG as a source of return, may mitigate the data limitations traditionally associated with ESG data.

Green Intangible Value

More economists now recognize the role of intangible capital as an important component of firm assets (see, for example, Corrado et al. 2009; Crouzet and Eberly 2018). The rise of intangible assets is particularly stark: Crouzet and Eberly (2018) report the fraction of intangibles as a fraction of total firm assets was around 10% in 1990 rising to close to 15% in 2016, and for high-tech firms, the fraction of intangible assets is now over 40% of total assets. Patents are one way of capturing intangible asset information: Since at least Hall et al. (1984), economists have estimated intellectual property using patent data, providing valuation information complementary to financial valuations captured using traditional earnings statements and balance sheets. In particular, several authors, like Hirshleifer et al. (2013), Bekkerman and Khimich (2017), and Lee et al. (2019), demonstrate the predictive power of patent data for cross-sectional equity returns.

In this section, we concentrate on green patents and show how they can be included as a measure of value. We collect data on global patents via Google

Exhibit 6
Relationship between Patents and R&D Spending



Notes: Data from Worldscope and Google simulation period: January 2000–September 2019. Past performance does not guarantee future results.

Patents Data, which is a rich database dating back to the 1980s.[7] We focus on green patents, which are patents promoting ESG-friendly innovations. These are defined as filing International Patent Classification (IPC) codes defined by the World Intellectual Property Organization if they meet UN Sustainable Development Goals (SDGs).[8] Examples of green patents include inventions around water and waste treatment, life-saving devices, fire-fighting advances, and clean energy. We take the two-year rolling sum of the number of green patents owned by each company divided by market capitalization. We match company names from the patent database to the standard financial databases using the methodology described in the Appendix. At the end of September 2019, the number of green patents totaled 6,637 across 401 companies, which clearly suggests that firms tend to have multiple patents. Most of the firms with patents are within materials (55), industrials (51), healthcare (49), and the fewest in financials (2). Taking the patents as a measure of intangible assets, we divide this by market capitalization to form an intangible green value signal and build a portfolio along the same lines as section, Factors and ESG Data, controlling for sector, industry, and country. Thus, the patents signal identifies companies within the same sector or industry that have more green patents than their peers.

Economic Intuition

The economic intuition of using green patents as an intangible measure of firm intrinsic value is as follows. First, patents are an important form of innovative output and they are traded and licensed in intellectual property markets (see Griliches 1990). Exhibit 6 shows the link between the patent signal and research and development (R&D) spending. R&D itself predicts future stock returns (see, for example, Lev et al. 2005). In some cases, patents are the direct product of R&D spending, but the lead-lag correlations between patents and R&D spending in Exhibit 6 suggest that R&D spending increases before the issuance of a patent

[7] There are hundreds of years of patent data. The first patent in the UK was issued in 1449 for the manufacture of stained glass and the first patent in the US was issued in 1790 for a process for making potash.

[8] For IPC codes, see https://www.wipo.int/classifications/ipc/en/ and for SDGs, see https:// sustainabledevelopment.un.org/sdgs. The SDGs are no poverty; zero hunger; good health and well-being; quality education; gender equality; clean water and sanitation; affordable and clean energy; decent work and economic growth; industry, innovation, and infrastructure; reduced inequalities; sustainable cities and communities; responsible consumption and production; climate action; life below water; life on land; peace, justice, and strong institutions; and partnerships for the goals.

(event time zero), and then there is continued spending in R&D after the patent is issued—suggesting a continued focus on innovation once the innovation is recognized in a patent.

The innovative output captured in patents is risky, however, as not all R&D results in commercial success. If we interpret patents as the capitalization of certain investments, with R&D devoted to patents being a form of investment following Cochrane (1991), then investors should earn returns for these additional risks in new, unproven inventions. The special focus on green patents is that the SDGs are not only areas that are important to society as recognized by the UN, efforts to solve them can also result in large profitable opportunities by firms.

Relation to Benchmark Value

Exhibit 7 documents the economic performance of intangible green value. Panel A graphs the cumulative relative performance of the green patents value factor portfolio versus the MSCI World Index from January 2000 to September 2019. As a comparison, we also graph the performance of the benchmark value factor portfolio. The intangible green value factor has an IR of 0.5 and has its strongest period from 2003 to 2011 with an IR of 0.94. There is a notable difference in performance with the benchmark value factor portfolio, based only on financial measures in the more recent period: From January 2007 to the end of the sample, the green value factor IR is 0.08 compared to −0.36 for regular value (see also Exhibit 1). This underperformance of the benchmark value factor portfolio coincides with the increasing importance of intangible capital noted by Crouzet and Eberly (2018).

Panel B reports some characteristics of the green value factor portfolio. The correlation of excess returns between green value and benchmark value is 15.7%, and thus there is some relation between the two. The fact that the correlation is much lower than one indicates that green value is not subsumed by regular value. We can test formally whether intangible green value is additive to the benchmark value factor by running a Britten-Jones (1999) spanning test, which yields a p-value of 0.003. Another way to look at potential overlap to benchmark value, as well as to other factors, is to measure the cross-sectional holdings correlations of green value to the other factors. We find an average negative correlation to all factors ranging from −1.2% to size, to −13% to low volatility. Panel B also shows the green patents factor portfolio has better sustainability characteristics than the benchmark value factor portfolio with the ESG score improved by 6.4% and the carbon emission intensity by 11%.

Corporate Culture Quality

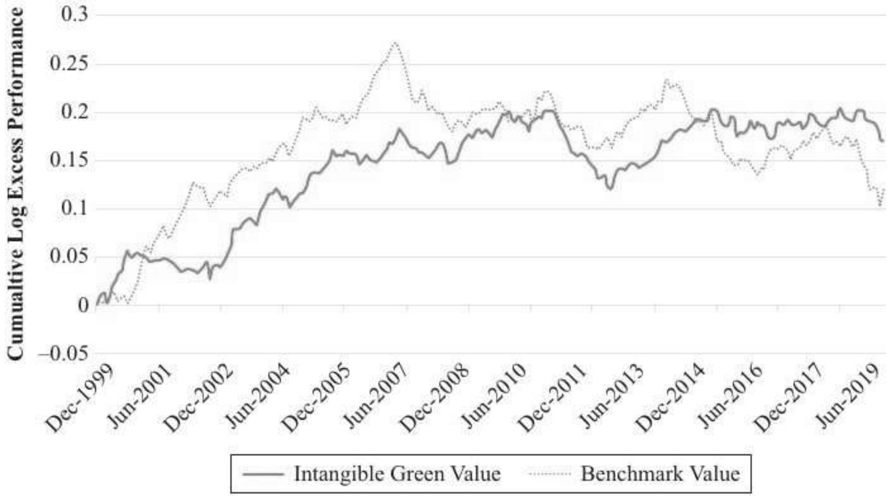
Since Kreps (1990) and, more recently, Bolton et al. (2012), economists have recognized the role of corporate culture in contributing to the production and value of firms.[9] Aspects of culture tend to be more qualitative compared to the more quantitative notions of financial quality, but recent advances by Guiso et al. (2015) and Li et al. (2019), among others, show that textual analysis (machine learning) techniques can be used to estimate corporate culture. In economic models, culture is relevant because it is a form of social norms and embeds values that are typically not formally specified, unlike contracts and legal norms—but they form an important part of G in ESG for firm value. Culture helps alleviate moral hazard: From employees' point of view, it helps internalize behaviors that accrue to the organization. For managers, corporate culture mitigates the urge to divert profits as breaches of trust lead to a breakdown of corporate norms. Because contracts are incomplete in the real world, culture matters. Not surprisingly, CEOs place the creation and maintenance of corporate culture as one of the most important facets in running companies (see Graham et al. 2019).

We follow Li et al. (2019) and use the word embedding model of Mikolov et al. (2013) to estimate the quality of corporate culture using conference call transcripts. We work with the five core corporate culture values identified by Guiso et al. (2015): innovation, integrity, quality, respect, and teamwork. Exhibit 8 illustrates how the word embedding model works. For each of the five core pillars, we specify a list of seed words. For example, a seed list containing words similar to *innovation* includes: creativity, excellence, passion, pride, etc. The word embedding algorithm finds words that are similar to the seed list using a deep neural network (for example LeCun et al. 2015).

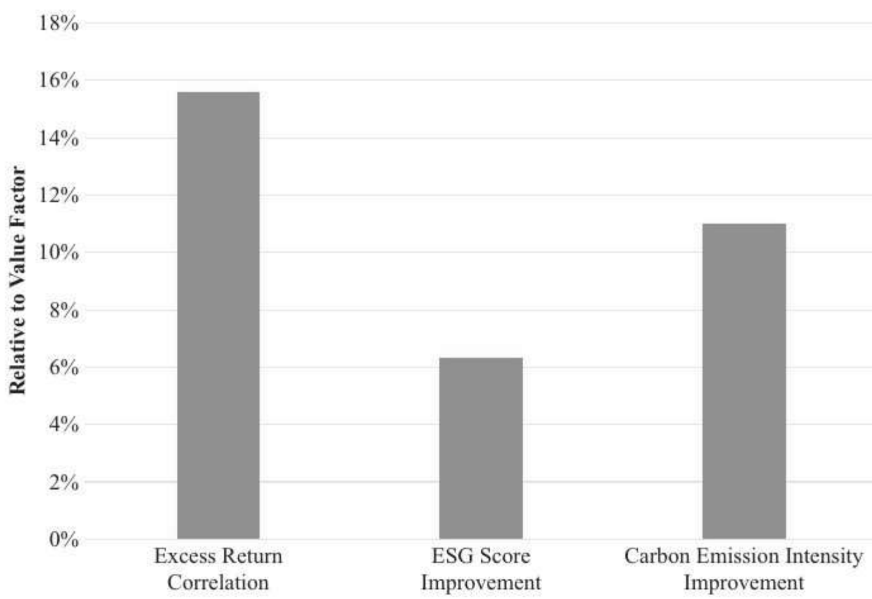
[9] A much larger organizational behavioral literature, building on social anthropology, has long studied positive and toxic corporate cultures. The classic textbook is Kotter and Heskett (1992). Zingales (2015) provides a literature review in the finance literature.

EXHIBIT 7
Intangible Green Value

Panel A: Cumulative Active Returns



Panel B: Characteristics of Intangible Green Value Factor Portfolio



Notes: Data from Worldscope, IBES, Google, and Barra period of returns shown: January 2000–September 2019. Past performance does not guarantee future results.

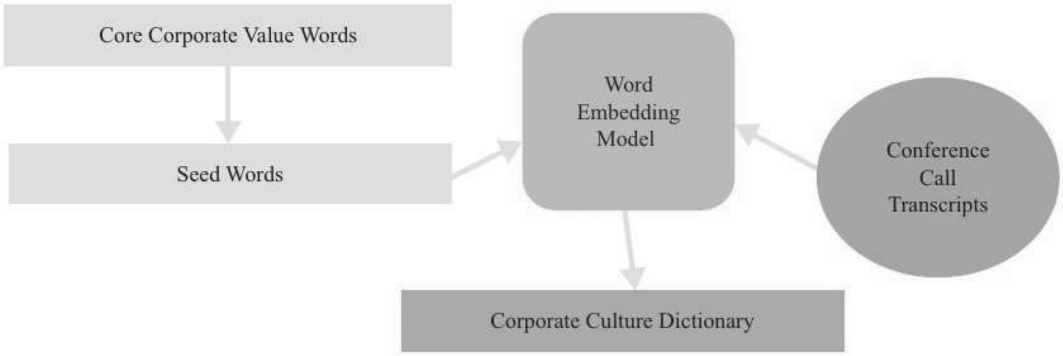
For example, related words to *passion* in the *innovation* pillar are found by analyzing call reports and are identified by the algorithm, with some examples being *dedication* and *creativity*. The full procedure then results in a dictionary of words based on the five culture pillars. We then count how often these words are mentioned in the call transcripts, adjusting for the total number of words within the transcript.

Relation to Benchmark Quality

Panel A of Exhibit 9 graphs the relative performance statistics of the corporate culture quality measure

EXHIBIT 8

Schematic of Measuring Corporate Culture Quality



Core Corporate Values	**Seed Words**
Innovation	Creativity, Excellence, Passion, Pride, Leadership, Growth, Performance, Efficiency, Results, Innovation
Integrity	Integrity, Ethics, Accountability, Honesty, Fairness, Responsibility, Transparency
Quality	Quality, Customer, Commitment, Dedication, Value, Expectations
Respect	Respect, Diversity, Inclusion, Development, Talent, Employees, Dignity, Empowerment
Teamwork	Teamwork, Collaboration, Cooperation

Source: Words are derived from Guiso et al. 2015. For illustrative purposes only.

versus the MSCI World Index from January 2007 to September 2019. Similar to our analysis for green intangible value (see Exhibit 7), Exhibit 9 also overlays benchmark quality that is constructed using only financial market data. The IR for corporate culture quality over the sample period is 0.29 with an annualized active risk of 2.4% and the traditional financial quality factor has an IR of 0.7 with active risk of 2.3%. We see relatively better performance of the corporate culture quality factor during the recovery post the global financial crisis, perhaps consistent with good corporate culture fostering cooperative opportunities among employees that tend to fare better during periods of recovery. Corporate culture quality fares worse going into the global financial crisis—a period where companies that focus more on cost reductions and operational efficiency, which are captured well by benchmark quality, tend to do better.

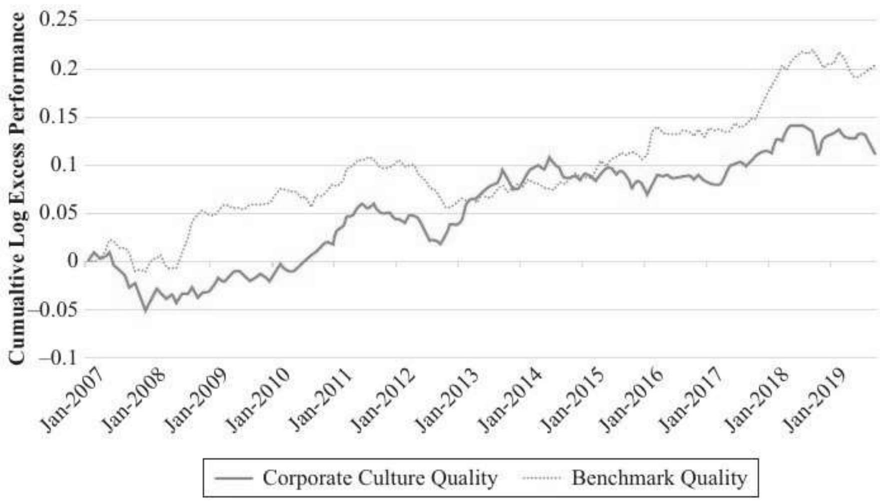
In Panel B, we report some characteristics of the corporate culture quality factor. Reflecting the overall similar payoff patterns in Panel A, the excess return correlation between corporate culture quality and traditional financial quality is 0.22, which suggests that corporate culture quality is related to, but different from, benchmark financial quality. We test the additivity of corporate culture to the benchmark quality factor by running the Britten-Jones (1999) statistic, which has a corresponding p-value of 0.068, which is close to, but not significant at the 5% level. Economically, the low correlation and the different dynamic behavior in Panel A indicate there are diversification benefits of the corporate culture quality factor to benchmark quality. Finally, we report the ESG and carbon characteristics of the corporate culture quality factor. The ESG score is similar to the quality benchmark (2% better) and, although the carbon emission intensity is 9.6% lower, it is still better than the market benchmark with an 18% improvement.

CONCLUSION

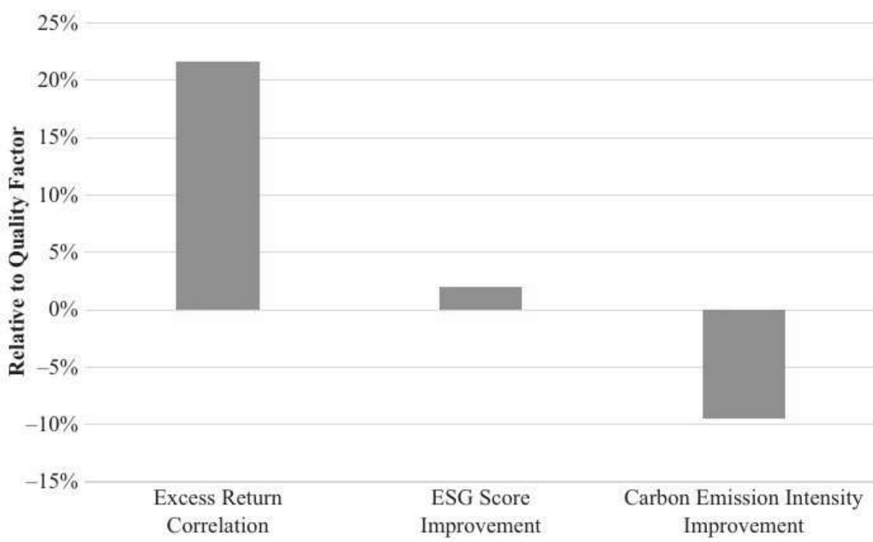
Environmental, social, and governance (ESG) risks can originate from the same economic rationales as regular style factors like value, momentum, quality, size, and low volatility: a reward for bearing risk, economic structural impediments, and behavioral biases. Certain ESG data may be linked to risk or behavioral sources of return that are consistent with factor premiums, and can be used together with traditional factor signals to obtain efficient factor exposure. Although traditional benchmark factors, which do not incorporate ESG information, are already ESG-friendly, the commonality

EXHIBIT 9
Corporate Culture Quality

Panel A: Cumulative Active Returns



Panel B: Characteristics of Corporate Culture Quality



Notes: Data from Worldscope, IBES, and Barra period of returns shown: January 2007–September 2019. Past performance does not guarantee future results.

between ESG and factor signals means that we can jointly optimize ESG, carbon, and factor exposures to form a multifactor portfolio with a 20% better ESG profile and 50% lower carbon reductions without exhibiting any detracting performance in historical data. We show that ESG data can be incorporated into the factor definitions themselves, with green intangible value, using green patents, and corporate culture quality, using machine learning on textual data, are additive to traditional value and quality benchmark factors.

APPENDIX

Portfolio Optimization

We construct benchmark factor portfolios using mean-variance optimization:

$$
\begin{aligned}
&Max\ \alpha_P - \frac{1}{2}\lambda\sigma_P^2 \\
&s.t.\quad w\,1 = 1 \\
&l_i \le w\,b_i \le u_i \\
&\quad w \ge 0
\end{aligned}
\tag{1}
$$

where α_p is the portfolio's active alpha; σ_p^2 is the portfolio's active risk; λ is a risk aversion parameter; w are the portfolio weights; 1 is a vector of ones; l_i, u_i are lower and upper bounds, respectively, with respect to characteristics *i*: country, sector, industry, and beta; and b_i are corresponding exposures of characteristic *i*. The scores are produced using standardized scores of the individual data items in the section, "Factor Data," and converted to alphas by multiplying by idiosyncratic volatility and a constant information coefficient (IC) of 0.05 following Grinold and Kahn (2000). For the multifactor portfolio, we use weights of 20% each to value, momentum, quality, size, and low volatility in the combined signal score of each stock.

To construct jointly optimized ESG and carbon improved factors, the optimization in equation (1), we add constraints that specify the ESG or carbon emission intensities (CE) must be improved by at least a certain minimum level, given by l_{ESG} and l_{CE}, respectively:

$$
\begin{aligned}
&w\,ESG \ge l_{ESG} \\
&w\,CE \le l_{CE}
\end{aligned}
\tag{2}
$$

Matching Names

The Google Patents data come with a large number of named entities holding patents, ranging from individuals to large corporations. The company names are not standardized and have different naming conventions to other traditional standardized data sets. We address this by first truncating the text into $k = 3$ length characters, shifting across by one character at a time, with the trigram length of three typically used for matching names/entities. We removed special characters and generic terms like *Corp.* or *Inc.* to help with the matching process.

We follow the term frequency inverse document frequency (TFIDF) procedure to convert the trigrams into vectors (see Jones 1972), which counts the frequency of each trigram. Similar company names will have a similar distribution of trigrams, which are formally matched with a cosine similarity measure. Multiple entries can also be accepted if the data used show potential of different naming schemes/practices of the same entity. We perform manual checks and also check robustness with different thresholds on the cosine similarity measure.

ACKNOWLEDGMENTS

The views expressed here are those of the authors alone and not of BlackRock, Inc. We thank Debarshi Basu and Andre Bertolotti.

REFERENCES

Ang, A. *Asset Management: A Systematic Approach to Factor Based Investing.* New York, NY: Oxford University Press. 2014.

Ang, A., R. H. Hodrick, Y. Xing, and X. Zhang. 2006. "The Cross Section of Volatility and Expected Returns." *The Journal of Finance* 61: 259–299.

Basu, S. 1977. "Investment Performance of Common Stocks in Relation to Their Price-Earnings Ratios: A Test of the Efficient Market Hypothesis." *The Journal of Finance* 32: 663–682.

Bekkerman, R., and N. Khimich. 2017. "Technological Similarity and Stock Return Cross-Predictability: Evidence from Patent Big Data." Working paper.

Berg, F., J. F. Koelbel, and R. Rigobon. 2019. "Aggregate Confusion: The Divergence of ESG Ratings." Working paper, MIT.

Bolton, P., M. Brunnermeier, and L. Veldkamp. 2012. "Leadership, Coordination, and Corporate Culture." *Review of Economic Studies* 80: 512–537.

Britten-Jones, M. 1999. "The Sampling Error in Estimates of Mean-Variance Efficient Portfolio Weights." *The Journal of Finance* 54: 655–671.

Cheng, I. H., H. Hong, and K. Shue. 2013. "Do Managers Do Good with Other Peoples' Money?" Working paper, Columbia University.

Clark, G. L., A. Feiner, and M. Viehs. 2015. "From the Stockholder to the Stakeholder: How Sustainability Can Drive Financial Outperformance." https://papers.ssrn.com/abstract_id=2508281.

Cochrane, J. H. 1991. "Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations." *The Journal of Finance* 46: 209–237.

Corrado, C., C. Hulten, and D. Sichel. 2009. "Intangible Capital and US Economic Growth." *Review of Income and Wealth* 55: 661–685.

Crouzet, N., and J. Eberly. 2018. "Understanding Weak Capital Investment: The Role of Market Concentrations and Intangibles." NBER Working Paper No. 25869.

Dechow, P., and R. Sloan. 1997. "Returns to Contrarian Investment Strategies: Tests of Naïve Expectations Hypotheses." *Journal of Financial Economics* 43: 3–27.

Dunn, J., S. Fitzgibbons, and L. Pomorski. 2018. "Assessing Risk through Environmental, Social and Governance Exposures." *Journal of Investment Management* 16: 4–17.

Eccles, R. G., I. Ioannou, and G. Serafeim. 2014. "The Impact of Corporate Sustainability on Organizational Processes and Performance." *Management Science* 60: 2835–2857.

Eccles, R. G., J. C. Stroehle. 2018. "Exploring Social Origins in the Construction of ESG Measures." Working paper, Said Business School.

Edmans, A. 2011. "Does the Stock Market Fully Value Intangibles? Employee Satisfaction and Equity Prices." *Journal of Financial Economics* 101: 621–640.

Fama, E. F., and K. R. French. 1993. "Common Risk Factors in the Returns of Stocks and Bonds." *Journal of Financial Economics* 33: 3–56.

——. 1996. "Multifactor Explanations of Asset Pricing Anomalies." *The Journal of Finance* 51: 55–84.

Frankel, R., and C. M. C. Lee. 1998. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics* 21: 283–319.

Friede, G., T. Busch, and A. Bassen. 2015. "ESG and Financial Performance: Aggregated Evidence from More than 2000 Empirical Studies." *Journal of Sustainable Finance & Investment* 5: 210–233.

Goetzmann, W. N., and S. Huang. 2018. "Momentum in Imperial Russia." *Journal of Financial Economics* 130: 579–591.

Graham, B., and D. Dodd. *Security Analysis*. New York, NY: McGraw-Hill. 1934.

Graham, J. R., J. Grennan, C. R. Harvey, and S. Rajgopal. 2019. "Corporate Culture: Evidence from the Field." https://ssrn.com/abstract=2805602.

Griliches, Z. 1990. "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature* 28: 1661–1707.

Grinold, R. C., and R. N. Kahn. *Active Portfolio Management*. New York, NY: McGraw-Hill. 2000.

Guiso, L., P. Sapienza, and L. Zingales. 2015. "The Value of Corporate Culture." *Journal of Financial Economics* 117: 60–76.

Hall, B. H., Z. Griliches, and J. A. Hausman. 1984. "Is There a Lag?" NBER Working Paper No. 1454.

Haugen, R., and N. Baker. 1996. "Commonality in the Determinants of Expected Stock Returns." *Journal of Financial Economics* 41: 401–439.

Hirshleifer, D., P. H. Hsu, and D. Li. 2013. "Innovative Efficiency and Stock Returns." *Journal of Financial Economics* 107: 632–654.

Hodges, P., K. Hogan, J. R. Peterson, and A. Ang. 2017. "Factor Timing with Cross-Sectional and Time-Series Predictors." *The Journal of Portfolio Management* 44: 30–43.

Hong, H., and M. Kacperczyk. 2009. "The Price of Sin: The Effect of Social Norms on Markets." *Journal of Financial Economics* 93: 15–36.

Jegadeesh, N., and S. Titman. 1993. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance* 56: 699–720.

Jones, S. K., 1972. "A Statistical Interpretation of Term Specificity and Its Application in Retrieval." *Journal of Documentation* 28: 11–21.

Kulkarni, P., M. Alighanbari, and S. Doole. 2017. "The MSCI Factor ESG Target Indexes: Single and Multiple-Factor Indexes with ESG Integration." Working paper, MSCI.

Kotter, J. P., and J. L. Heskett. *Corporate Culture and Performance*. New York, NY: Free Press. 1992.

Kreps, D. "Corporate Culture and Economic Theory." In *Perspectives on Positive Political Economy*, edited by J. E. Alt and K. A. Shepsle, 93-104. Cambridge, UK: Cambridge University Press. 1990.

Lakonishok, J., A. Shleifer, and R. Vishny. 1994. "Contrarian Investment, Extrapolation, and Risk." *The Journal of Finance* 44: 1541–1578.

LeCun, Y., Y. Bengio, and G. Hinton. 2015. "Deep Learning." *Nature* 521: 436–444.

Lee, C. M. C., S. T. Sun, R. Wang, and R. Zhang. 2019. "Technological Links and Predictable Returns." *Journal of Financial Economics* 132: 76–96.

Lettau, M., and J. A. Wachter. 2007. "Why Is Long-Horizon Equity Less Risky? A Duration-Based Explanation of the Value Premium." *The Journal of Finance* 62: 55–92.

Lev, B., B. Sarath, and T. Sougiannis. 2005. "R&D Reporting Biases and Their Consequences." *Contemporary Accounting Research* 22: 977–1026.

Li, K., F. Mai, R. Shen, and X. Yan. 2019. "Measuring Corporate Culture Using Machine Learning." Working paper. https://ssrn.com/abstract=3256608

Madhavan, A., A. Sobcyzk, and A. Ang. 2018. "What's in Your Benchmark? A Factor Analysis of Major Market Indexes." *The Journal of Index Investing* 9: 66–79.

Melas, D., Z. Nagy, and P. Kulkarni. 2016. "Integrating ESG into Factor Portfolios." MSCI Research Insight.

Mikolov, T., I. Sutskever, K. Chen, G. S. Corrado, and J. Dean. 2013. "Distributed Representations of Words and Phrases and Their Compositionality." In *Advances in Neural Information Processing Systems 26*, edited by C. J. C. Burges, L. Bottou, M. Welling, Z. Ghahramani, and K. Q. Weinberger. *NIPS 2013 Proceedings.*

MSCI ESG Research. 2019. MSCI ESG Ratings Methodology.

Northern Trust. 2014. "Doing Good and Doing Well—How Quality Can Enhance Your ESG Strategy." Working paper.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108: 1–28.

Piotroski, J. D. 2000. "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers." *Journal of Accounting Research* 38: 1–41.

Ratcliffe, R., P. Miranda, and A. Ang. 2017. "Capacity of Smart Beta Strategies from a Transaction Cost Perspective." *The Journal of Index Investing* 8: 39–50.

Ross, S. A. 1976. "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory* 13: 341–360.

Sloan, R. 1996. "Do Stock Prices Reflect Information in Accruals and Cash Flows About Future Earnings?" *Accounting Review* 71: 289–316.

Zingales, L. 2015. "Does Finance Benefit Society?" NBER Working Paper No. 20894.

ADDITIONAL READING

Capacity of Smart Beta Strategies from a Transaction Cost Perspective
RONALD RATCLIFFE, PAOLO MIRANDA, AND ANDREW ANG
The Journal of Index Investing
https://jii.pm-research.com/content/8/3/39

ABSTRACT: *Using a transaction cost model and an assumption for the smart beta premium observed in data, the authors estimate the capacity of a particular implementation of momentum, quality, value, size, minimum volatility, and a multifactor combination. For a given trading horizon, they can find the fund size at which the transaction costs from flows into these strategies negate the smart beta premium. For a one-day trading horizon, momentum is the strategy with the smallest assets under management (AUM) capacity of $65 billion, and size is the largest with an AUM capacity of $5 trillion. At five days, momentum and size capacity rise to $320 billion and over $10 trillion, respectively.*

What's in Your Benchmark? *A Factor Analysis of Major Market Indexes*
ANANTH MADHAVAN, ALEKSANDER SOBCZYK, AND ANDREW ANG
The Journal of Index Investing
https://jii.pm-research.com/content/9/2/66

ABSTRACT: *The authors examine the factor exposures of several popular market-capitalization indexes and how they vary over time. The authors find that most market-capitalization-weight indexes are effectively exposed to only two or three factors, with value and momentum being increasingly dominant. They find that the proportion of index movements explained by factors has materially increased in recent years, which is consistent with a more top-down, macro-driven environment or the increasing importance of economy-wide risks for financial markets.*

Factor Timing with Cross-Sectional and Time-Series Predictors
PHILIP HODGES, KED HOGAN, JUSTIN R. PETERSON, AND ANDREW ANG
The Journal of Portfolio Management
https://jpm.pm-research.com/content/44/1/30

ABSTRACT: *What smart beta strategy should investors use and when? The authors search for predictors of value, size, momentum, quality, and minimum-volatility smart beta factors under different economic regimes and market conditions. They find that combining information from several predictors such as business cycle indicators, valuation, relative strength, and dispersion metrics is more effective than using individual predictors.*