Is There a Green Factor?

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Worldwide awareness of environmental degradation has increased recently as well as a growing sense of urgency about environmental preservation. These concerns are reflected in new policies and regulations intended to reduce the ecologically damaging effects of production processes. The Kyoto Protocol, European Emissions Trading Scheme, and U.S. Environmental Protection Agency Clean Air Act are examples of policies aimed at protecting the environment. As the cost of pollution increases, companies are finding ways to mitigate the potential associated financial risk by adapting to a low-carbon operating environment. At the same time, greater environmental awareness is gradually transforming consumer behavior and spawning new industries to focus on the provision of ecologically friendly alternative solutions.

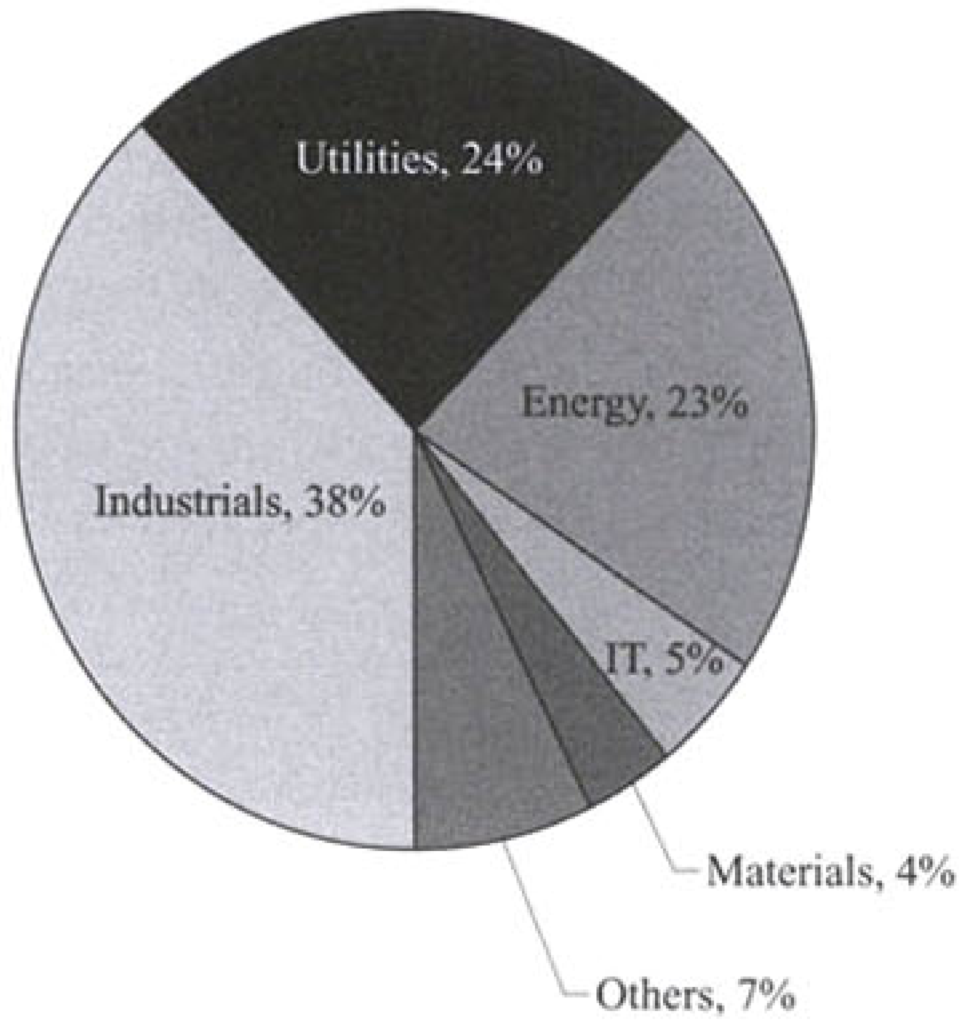
Climate change has far-reaching implications for the global economy and is being recognized as a long-term investment theme. As more investors take note of companies that are well positioned to handle climate change, a common factor may account, in part, for the share prices of these companies. This article addresses the question of whether returns to firms that are beneficiaries of climate change display common properties not captured by risk factors in use today. In other words, is there a green factor?

THE RENEWABLE ENERGY SAMPLE PORTFOLIO

Given the exploratory nature of the study, we focused our analysis on companies whose businesses are directly or indirectly involved in the provision of renewable energy. We chose renewable energy firms because they are direct beneficiaries of climate change and represent pure plays of climate-change investing.

Our sample comprised 84 stocks sourced from 21 countries and drawn mainly from the industrial, utility, energy, information technology (IT), and materials sectors. Industrial sector firms are mainly involved in the production of electrical equipment associated with the generation of renewable energy. Firms in the utility sector are directly involved in the generation of renewable energy. The companies in the IT sector manufacture hardware and software used in solar and other types of alternative energy applications. In the materials sector, relevant firms provide inputs to renewable energy production (e.g., chemical reagents for the synthetic fuels industry) and outputs from renewable sources. The geographical distribution of the sample was 32% in U.S. firms, 26% in Eurozone firms, and 15% in firms in the emerging markets, including Russia.

EXHIBIT 1
GICS Sector and Country for Selected Firms with Renewable Energy Activities



Country	No. of Stocks
USA	27
Germany	13
United Kingdom	6
Canada	5
France	4
Australia	4
Taiwan	3
Brazil	3
Denmark	3
Italy	2
Switzerland	2
Philippines	2
Poland	2
Belgium	1
Hong Kong	1
Russia	1
Norway	1
Greece	1
Thailand	1
Indonesia	1
Spain	1
	84

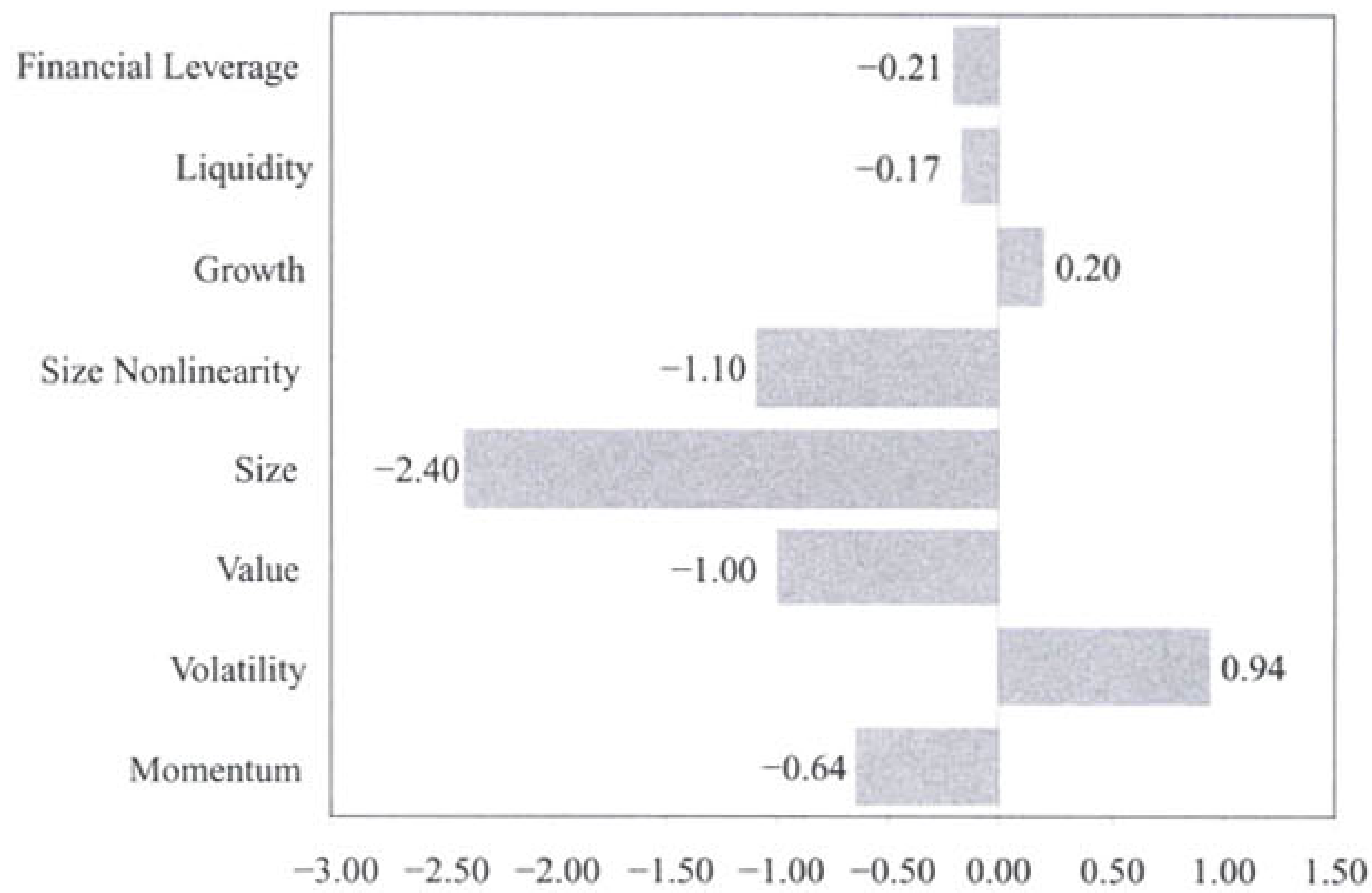
Source: MSCI Barra.

RISK CHARACTERISTICS OF THE RENEWABLE ENERGY PORTFOLIO

We began by examining the risk characteristics of an equal-weighted renewable energy portfolio using the new and enhanced Barra Global Equity Model (GEM2). The portfolio's exposures to the model's eight Barra style factors—value, growth, momentum, volatility, size, size nonlinearity, financial leverage, and liquidity[1]—yielded information on how the renewable energy stocks compare with the rest of the global equity universe. By construction, a portfolio's exposure to a factor represents the sensitivity of its value to that factor. Exposures were normalized over the GEM2 estimation universe so that the average exposure is zero; for example, an exposure of –2.0 is two standard deviations below the average.

The results presented in Exhibit 2 show that the renewable energy stocks are notably below average in size, size nonlinearity, value, and momentum, but are above average in terms of volatility. These stocks, therefore, tend to be relatively small and tend not to be value stocks, but do tend to be relatively more volatile than other stocks. These characteristics appear to be consistent over time as well as with our understanding of renewable energy firms, which tend to be young growth companies with volatile stock prices.

EXHIBIT 2
Exposures to Barra Risk Factors in Barra GEM2 Model (Averages of Monthly Exposures, September 2007–August 2008)



DO COMMON RISK FACTORS EXPLAIN THE PERFORMANCE OF THE RENEWABLE ENERGY PORTFOLIO?

Exhibit 3 plots the cumulative total returns of the sample portfolio against the MSCI All Country World Index (MSCI ACWI Index) and the MSCI All Country

World Energy Index (MSCI ACWI Energy Index) over the past three years (May 2005 to May 2008). The exhibit shows that the sample portfolio recorded a significant performance differential compared to the broader benchmark indices.

Before we tested for the existence of a green factor, we examined whether existing common risk factors could sufficiently explain the performance of the renewable energy portfolio. Based on the portfolio risk attribution using GEM2, the renewable energy firms in the sample tended to be below average in size, which led to the question of whether the small-cap characteristic might explain their superior performance. One simple way to control for this effect is to replace the MSCI ACWI Index shown in Exhibit 3 with the MSCI ACWI Small Cap Index. We also considered other aspects of style by examining the performance of small-cap value and growth indices.

Exhibit 4 compares the performance of the sample portfolio with the various small-cap versions of the MSCI ACWI Index. The shaded curve represents the MSCI ACWI Small Cap Index, which is sandwiched between the MSCI ACWI Small Cap Value and Growth Indices. The performances of the three small-cap indices were not significantly different, implying that the style effects considered are limited compared to the performance dif-

EXHIBIT 3
Performance of Sample Portfolio and MSCI Indices

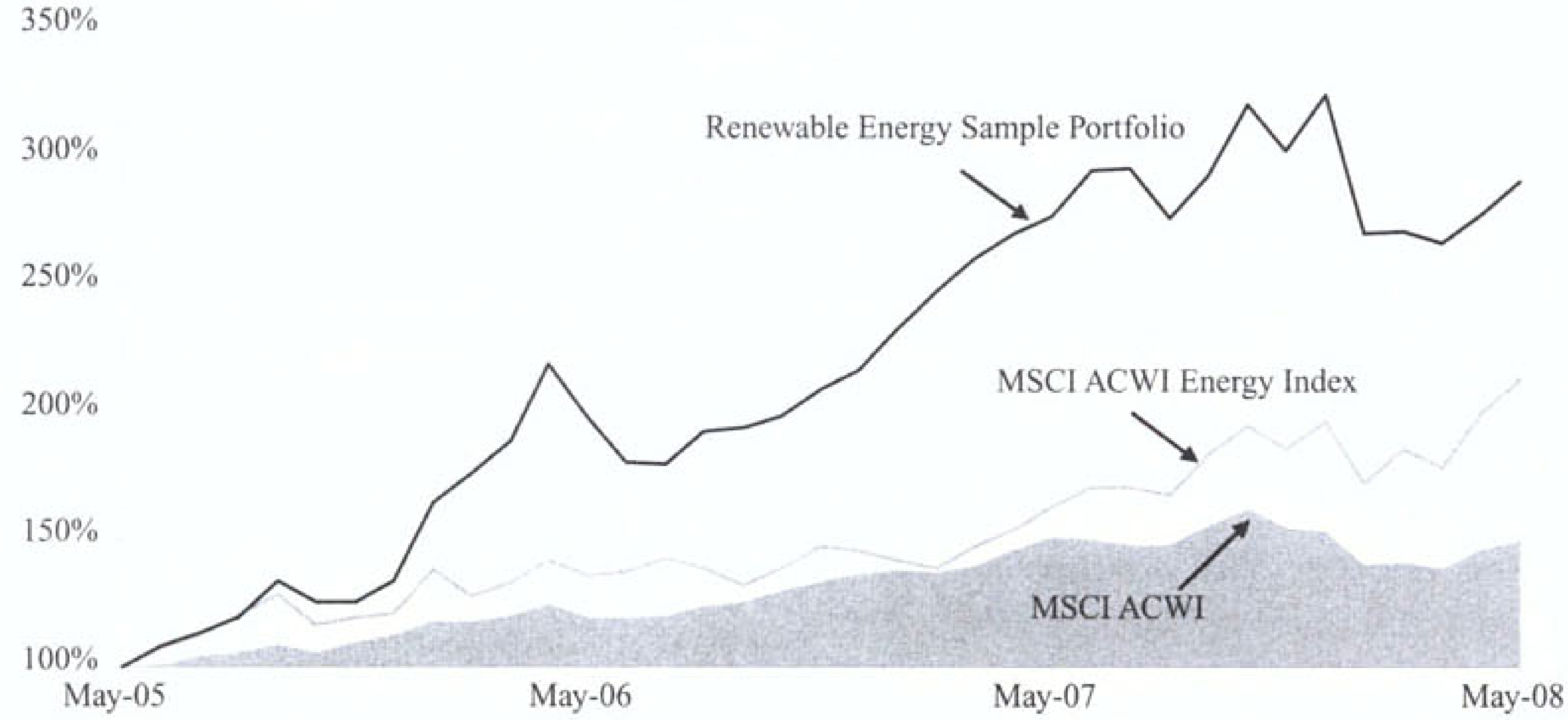
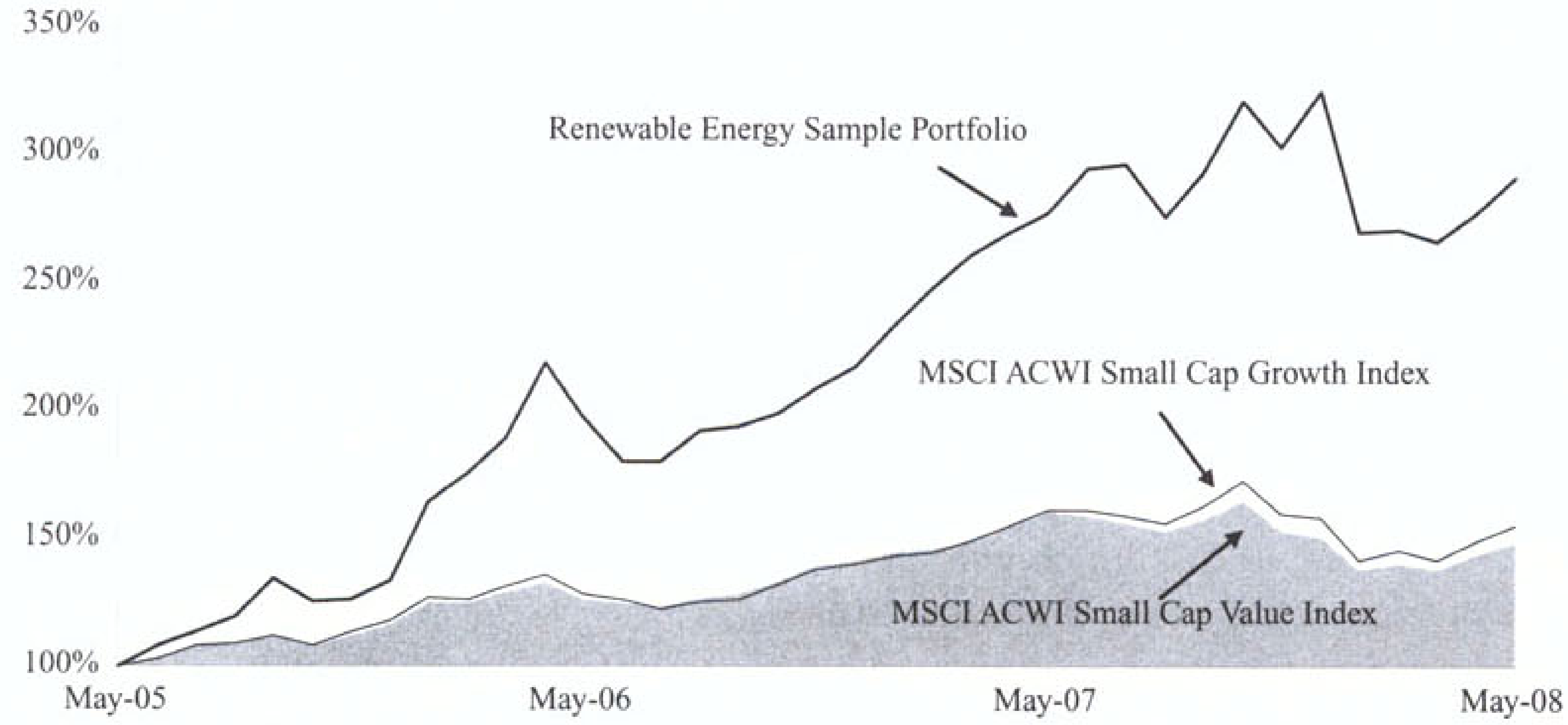


EXHIBIT 4
Performance Compared to MSCI ACWI Small Cap Indices



ferential with the sample portfolio of renewable energy stocks.

Another way to analyze the impact of size on performance is to compare the relative performance of small-cap and large-cap stocks within the sample portfolio. To do this we compared the equal-weighted renewable energy portfolio with a version weighted by free float-adjusted market capitalization. The two versions of the portfolio are shown in Exhibit 5. From mid-2005 to early 2007, a period when small caps outperformed large caps, the cap-weighted version lagged the equal-weighted version. But in the latter half of 2007, in the later stages of the bull market, large-cap stocks fared much better so that the cap-weighted portfolio ended the three-year period from May 2005 to May 2007 outperforming its equal-weighted counterpart. These results support the conclusion that firm size cannot account for the superior performance of renewable energy stocks.

Finally, we investigated whether the difference in country distribution is a major factor in the results. This is a possibility because in the sample renewable energy portfolio the share of firms in the emerging markets is somewhat higher than that in the MSCI ACWI Index. In addition, the country weights tend to be more variable over time due to the relatively small number of stocks in the portfolio. To account for this effect, we used composite small-cap indices of the countries represented in our sample portfolio and weighted them according to the actual country weights in the portfolio. This was implemented from the start of the sample period and repeated on a monthly basis. At the monthly rebalancing points, the weights of the composite small-cap index were reset to the corresponding country weights in the sample portfolio. This created a geographically comparable index capable of accounting for differences in country distribution while still controlling for the size effect through the use of small-cap indices.

The country-adjusted small-cap index and the MSCI ACWI Index are shown in Exhibit 6 with the equal-weighted and cap-weighted versions of the sample portfolio. The country adjustment appears to have improved the performance of the MSCI ACWI Small Cap Index, but the effect is not sufficiently large to account for the performance differential with the sample portfolio. Therefore, the observations to this point suggest that a more rigorous statistical test is warranted.

GREEN INDUSTRY FACTOR EVIDENCE IN RISK MODELS

To test for a green industry factor, we analyzed the specific return data of GEM2 to determine if any residual information could be extracted. We constructed exposures by assigning a one to green stocks and a zero to the remaining stocks in the estimation universe. We standardized these exposures to have a regression-weighted mean of zero. Finally, we regressed the specific, weekly returns on the exposures to obtain an estimate of the green factor return.

EXHIBIT 5
Equal-Weighted vs. Float-Adjusted Cap-Weighted Indices

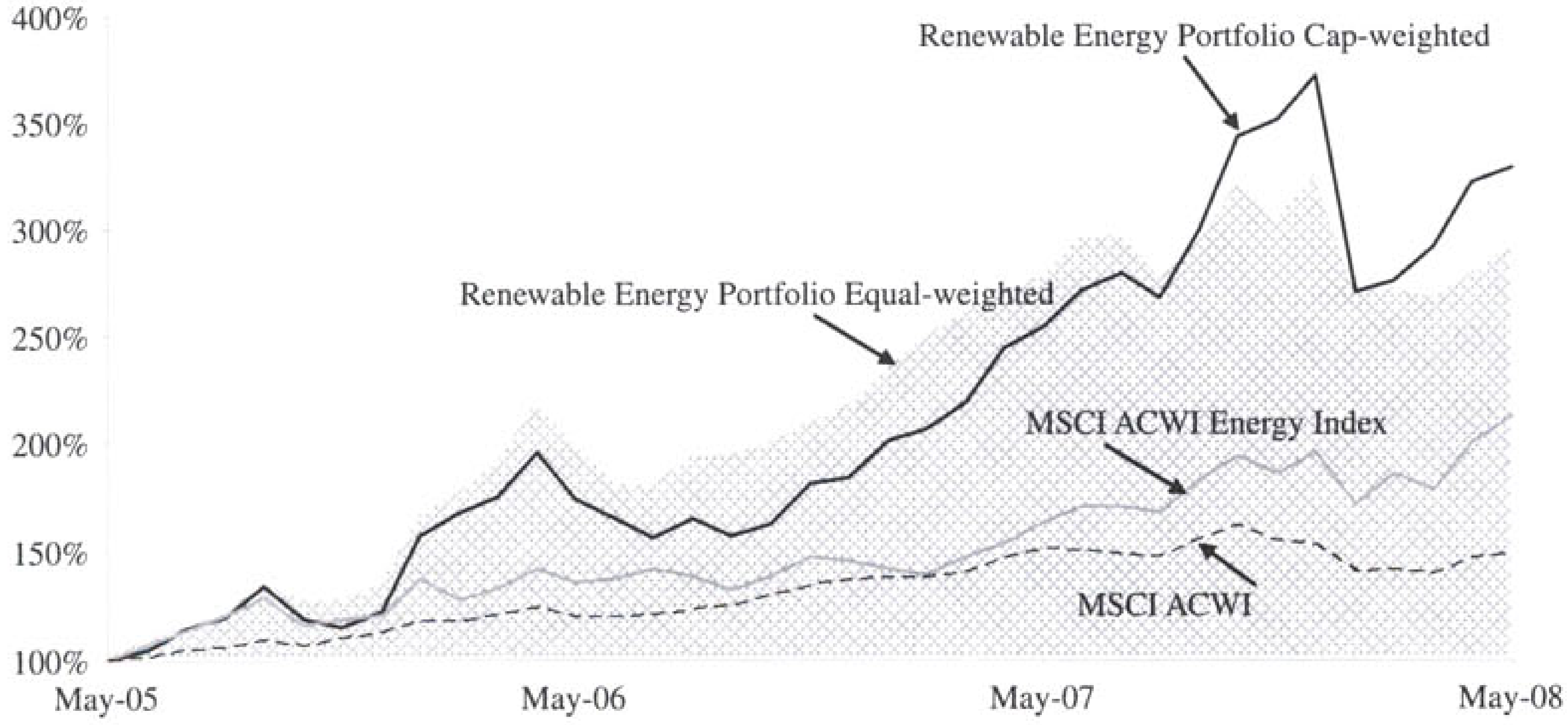


EXHIBIT 6
Adjusting for Country Distribution Differences with Benchmark

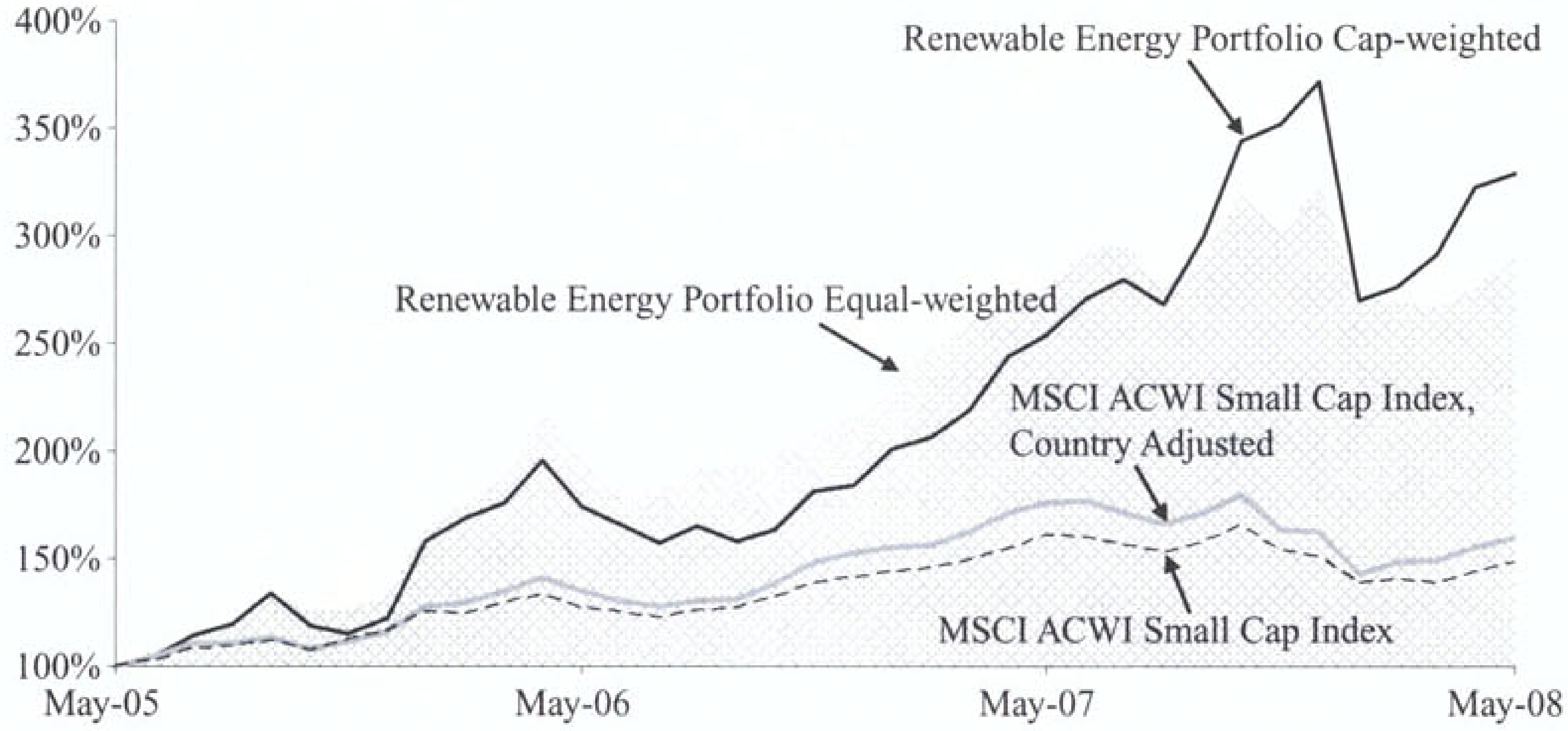
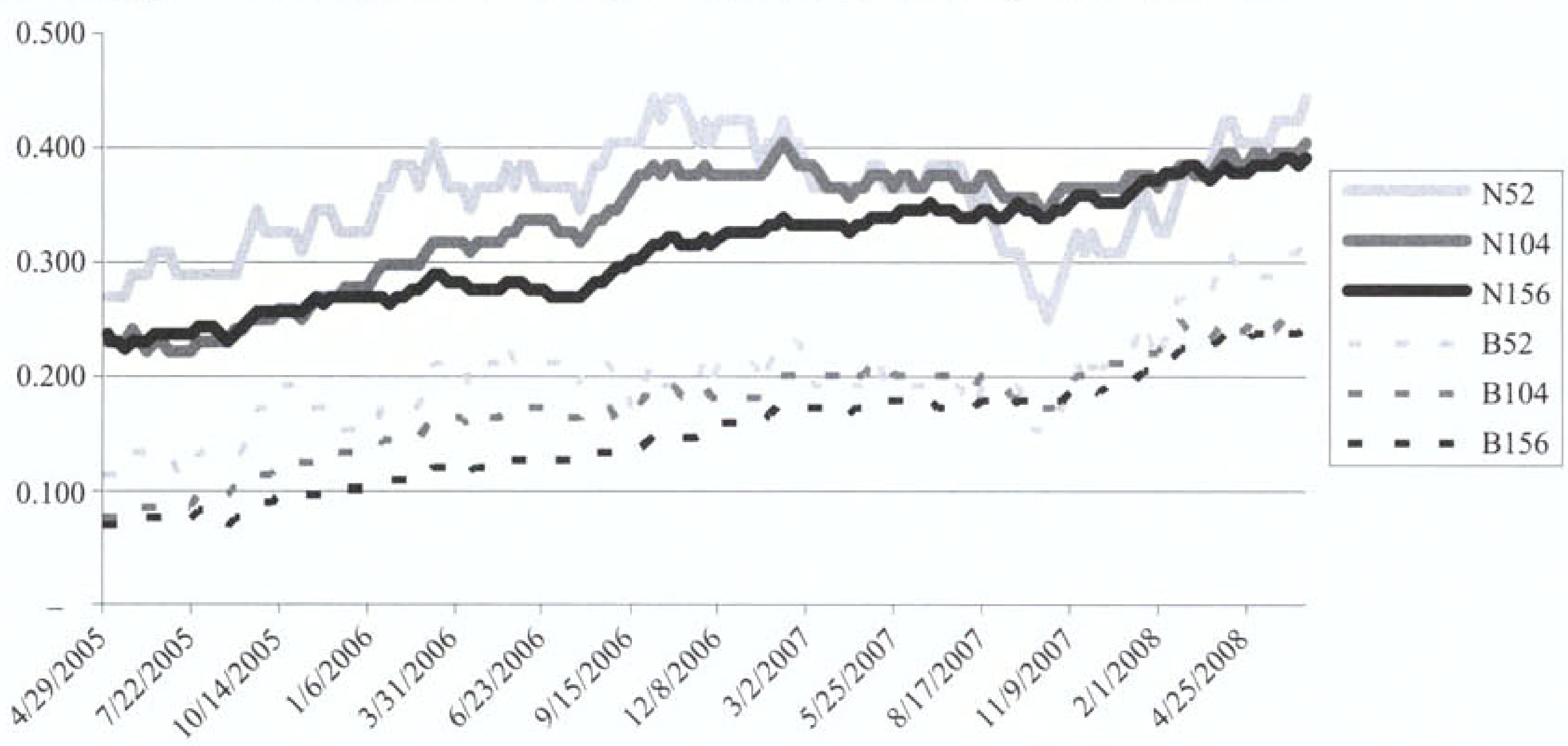


EXHIBIT 7
Trailing Ratio of Significant Regressions Using Normal and Bootstrap Distributions



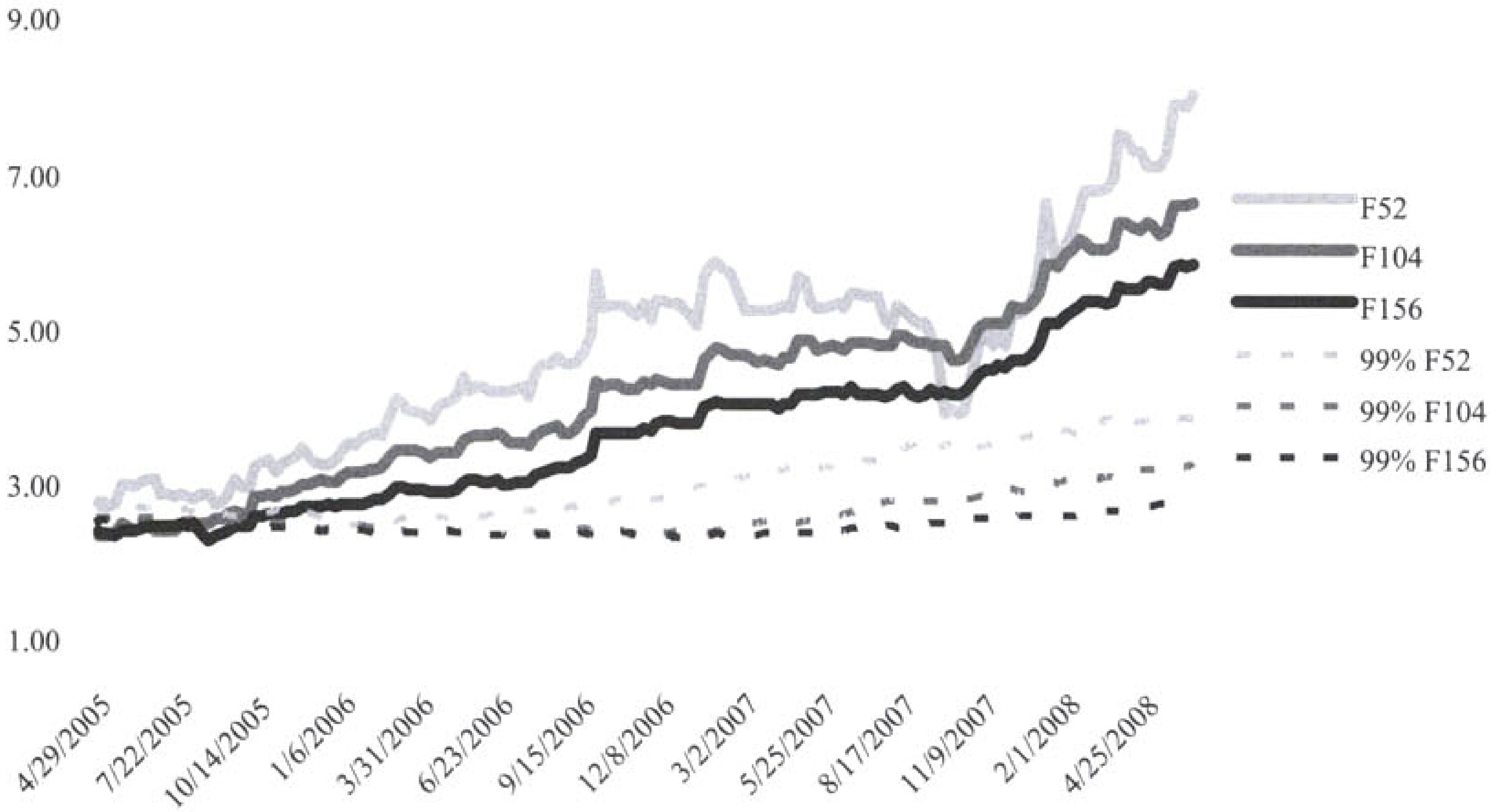
We used the t-ratio, the factor return estimate divided by its estimated standard deviation, to evaluate the statistical significance of the green factor return. Under the null hypothesis—i.e., there is no green factor—the t-ratio has approximate 2.5% and 97.5% critical values of –2 and 2, respectively, under the assumption that GEM2 residuals are normally distributed. Consistently larger t-ratios imply the presence of a green factor. To study the significance of the factor returns, we computed the fraction of absolute t-ratios greater than 2 in rolling windows of 52, 104, and 156 weeks, which are shown as solid lines in Exhibit 7. A value of 0.30 compares favorably with similar statistics of some GEM2 industries.

To avoid relying on normality assumptions for the distribution of the t-ratio, we used a bootstrap methodology. Our idea was that random sampling from the empirical distribution of the specific returns would produce a sample with identical noise to the true dataset, but would wash out any green factor component.

In the bootstrap method, specific returns are independently drawn at random (with replacement) for each firm in the estimation universe. Repeating the cross-sectional

EXHIBIT 8

Trailing-Mean *t*-Squared Statistic and Its 99% Bootstrap Critical Value



regressions over 1,000 bootstrap runs, we obtained the distribution of the t-ratio for each week. This distribution yielded larger critical values than the normal distribution, which made it harder to reject the null hypothesis of statistical insignificance, and resulted in a substantial drop in the ratio of significant regressions represented by the dotted lines in Exhibit 7. With more than 20% of t-ratios exceeding these more rigorous critical values, however, there is statistical evidence showing the emergence of a green factor.

To judge the overall quality of the regressions, we computed 52-, 104- and 156-week trailing-mean t-squared statistics. Under the assumption of normality, this statistic exceeds four with a 95% significance level. In addition, we used the bootstrap distribution to compute 99% critical values. Exhibit 8 shows the three rolling-mean t-squared statistics (solid lines) and the bootstrap critical values (dotted lines). We observed an increasing trend in the overall significance, further supporting our conclusion that a green factor exists.

Therefore, even with the higher statistical bar of the bootstrap method, in about a quarter of the weekly returns over the three-year period from May 2007 to May 2008, the green stocks exhibited common behavior. This number is substantially higher than the 5% expected by pure chance with the chosen significance level.

SUMMARY

In this article, we have presented our investigation of the unique risk and return characteristics of green stocks, including a study of renewable energy companies. Using the Barra Global Equity Model, or GEM2, we found that renewable energy firms are generally smaller and more volatile than the market on average, and have a negative value tilt. In addition, the impact of firm size, sector, style, and geographical distribution do not fully account for the superior performance of these firms. Finally, controlling for all GEM2 risk factors, we found that a statistically significant green factor seems to have emerged in recent years. These preliminary findings warrant further investigation of the risk and return characteristics of green portfolios.

ENDNOTE

[1]The value factor is based on earnings to price, forecast earnings to price, book to price, cash earnings to price, and dividend yield. The growth factor, which differentiates stocks based on their prospects for sales or earnings growth, is computed from various measures of earnings or sales growth. The momentum factor identifies recently successful stocks using price behavior in the market as measured by relative strength

and historical alpha. The volatility factor differentiates stocks according to their relative volatility, as determined by their historical sigma, historical beta, cumulative range, and daily standard deviation. The size factor values companies according to their market capitalization, differentiating between large and small companies. The nonlinear size factor captures nonlinearities in the payoff to the size factor across the market-cap spectrum. The financial leverage factor differentiates between highly leveraged stocks with those having low leverage, and is based on various liability ratios. Lastly, the liquidity factor captures differences in stock return due to variation in trading activity, as determined by turnover measured over various time scales.