Fundamental Indexing Around the World

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ABSTRACT

Using an international sample from 1982 to 2008, we investigate the performance of global and 50 country-specific (28 developed and 22 emerging) fundamentally weighted portfolios compared to capitalization-weighted portfolios. First, we establish that superior performance of domestic portfolios diminishes considerably when applying a bootstrap procedure for robust performance testing. Second, after controlling for data snooping biases and the value premium, we find evidence of outperforming global fundamental indexes, but no compelling evidence of outperforming country-specific indexes.

Keywords: Fundamental Indexing · Value Premium · Performance Evaluation

JEL Classification: G11 · G14 · G15

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"It's a triumph of marketing, and not of new ideas. It's a repackaging of old ideas. [...] The academics have been well aware of these issues for 15 years. It's just value vs. growth."

Fama and French (2007)

"The development of fundamentally indexed portfolios may offer an answer to some of the deficiencies of capitalization-weighted indexes."

Siegel (2007)

1. Introduction

The standard for weighting is the market capitalization-weighted portfolio: a portfolio that weights each component by its stock price multiplied by its common shares outstanding. This methodology has strong appeal since the return of these portfolios represents the aggregated average market return to all shareholders. However, one essential question is ordinarily overlooked in this context: Does the predominant weighting scheme for portfolios – market capitalization – really suit investor's needs? In other words: can a capitalization-weighted portfolio provide the best available risk and return relation for an investor?

This provocative concept of fundamental indexing by Arnott, Hsu, and Moore (2005) has led to a new debate about this question.[1] The approach allocates capital to stocks based on the weights of metrics such as book value, cash flow, dividends, and sales.

In this paper, we provide the first comprehensive worldwide assessment of fundamental weighted portfolios on a global and country-based level applying the Ledoit and Wolf (2008) bootstrap procedures for robust performance testing and the Romano and Wolf (2005) data snooping control. In this way, we develop a fresh and careful insight to the question whether a weighting scheme based on fundamentals or market capitalization is superior. This question is important on a methodological level because researchers frequently use specifically weighted portfolios (usually, value-weighted or equal-weighted), as for example, for event studies, and performance evaluation. Also, it is well established in the literature that passive investing outperforms active investing (see, e.g. Jensen, 1968; Malkiel, 1995; Carhart, 1997; French, 2008). Thus, it is of interest whether fundamental indexes can really challenge capitalization-weighted indexes as the prevailing passive investing paradigm.

The primary theoretical rationale for the capitalization weighting scheme is rooted in the Capital Asset Pricing Model (CAPM) of Sharpe (1964), Lintner (1965),

[1] With, for example, Jeremy Siegel as a proponent (see 'The Noisy Market Hypothesis', Wall Street Journal, June 14, 2006), and John Bogle and Burton Malkiel as opponents of fundamental indexing (see 'Turn on a Paradigm?', Wall Street Journal, June 27, 2006). For the history of fundamental indexing, see Siegel (2007).

and Mossin (1966), which establishes that an investor can have no better risk and return trade-off than that available by holding a portfolio consisting of all risky assets in the following proportion: that each asset in the market portfolio equals the market value of the asset divided by the total market value of all assets. Hence, a capitalization-weighted portfolio of all tradable securities should be mean-variance optimal. Regardless of the theoretical rationale, this inference is questionable. For example, Markowitz (2005) examines the assumptions that underlie the CAPM theory and finds several aspects that question the robustness of the expectation that a capitalization-weighted market portfolio is mean-variance optimal: when one clearly unrealistic assumption of the model is replaced by real-world constraints, this conclusion no longer holds.

Additionally, the prediction of the CAPM depends critically on market efficiency. The Efficient Market Hypothesis assumes that the price of a stock at every point in time represents the best, unbiased estimate of firm value. Hsu (2006) argues that if stocks are mispriced in the sense that they do not fully reflect firm fundamentals, the traditional capitalization weighting scheme leads to suboptimal performance. This is because underpriced stocks will have smaller capitalizations than their fair equity value, and similarly, overpriced stocks will have larger capitalizations than their fair equity value. Thus, the sub-optimality arises because capitalization weighting tends to overweight stocks whose prices are high relative to their fundamentals and underweight stocks whose prices are low relative to their fundamentals. Treynor (2005) formally demonstrates that market-valuation-indifferent portfolios are superior to capitalization-weighted portfolios because their weights do not suffer from the error in market prices. It follows that market-valuation-indifferent portfolios will mitigate the problem of overweighting overvalued stocks and underweighting undervalued stocks.

However, the theoretical superiority of market-valuation-indifferent portfolios has been questioned. Perold (2007) criticizes the theory on which fundamental indexing is based, that is, that an investor can beat the market without knowing fair value simply by avoiding the capitalization weighting scheme. If one does not know fair value, then even though prices can move toward fair value, the direction of that movement is random. He argues that if markets are inefficient, but one does not know whether a given stock is over- or undervalued, then there is no performance drag from capitalization weighting. Another way to state the preceding conclusion is in terms of the correlation of the pricing error with fair value and with market value. If a fundamentally weighted portfolio is to outperform a capitalization-weighted portfolio of the same stocks, then the fundamental variables used to construct the weights should contain more information about the fair values of the stocks than the market values of the stocks contain. Kaplan (2008) therefore develops a boundary condition that needs to be satisfied in order for a non-capitalization weighting scheme to add value: if the correlation between the fundamental values and the fair values exceeds the correlation between the market values and the fair values, then fundamental weighting is the a priori superior approach. If the reverse is true, then capitalization weighting is superior. Since fair values in these inequalities are not observable, one can only evaluate the historical performance to see whether fundamental weighting or capitalization weighting is the better way of investing.[2]

Previous empirical research on fundamental weighted portfolios can be categorized into three groups: alternative inference of fundamental values without using accounting data, re-weighting of originally capitalization-weighted indexes by fundamentals, and analysis of commercially available fundamental indexes.

Chen, Chen, and Bassett (2007) show how to implement the idea of fundamental weighted portfolios without directly measuring fundamental values. They are indeed influenced by Arnott, Hsu, and Moore (2005), but the estimation of fundamental weights based on accounting data is thereby replaced by a smoothed average of traditional capitalization-weights. Assuming that market prices are unbiased, but noisy approximations for fundamentals, they find an outperformance over the traditional capitalization-weighted portfolio on the U.S. market by about one percent a year.

Arnott, Hsu, and Moore (2005) are further supported by Hemminki und Puttonen (2008), who re-weight the constituents of the Dow Jones Euro Stoxx 50 by fundamentals, as well as by Stotz, Döhnert, and Wanzenried (2007), who perform a similar study for the broader European stock market index, the Dow Jones Stoxx 600.

[2] Arnott (2004) poses interesting questions which apply to fundamental indexing as well: “When theories do not agree, though, should we discard the messier one? Not if we accept the wisdom of Einstein, requiring our theories to be no simpler than necessary. If finance theory assumes that markets are efficient, and behavioral finance suggests that markets are not efficient, do we discard the less convenient theory?”

Estrada (2008) concludes that investors willing to abandon capitalization-weighted indexes in favor of other alternatives should look into traditional value (particularly, dividend-yield-weighted) strategies, which seem to outperform fundamental indexing (hence, price-unrelated) strategies.

Using the Fama and French (1993) three-factor model, Jun and Malkiel (2008) assess the performance of one commercially available fundamental index, the FTSE RAFI US 1000, and show that it exhibits a significant value tilt, and that the alpha of this particular index is not statistically significantly different from zero.[3] Amenc, Goltz, and Le Sourd (2009) analyze and compare the performance of commercially available fundamental indexes of seven different index providers for the U.S. market and find in most cases no significant outperformance over capitalization-weighted indexes.

In contrast to previous research, we provide in this paper the first comprehensive worldwide assessment of fundamental weighted portfolios on a global and country-based level. While prior studies in this field obtained their results generally by applying a traditional performance measurement framework, we are the first, to the best of our knowledge, to assess the performance of fundamentally weighted portfolios by applying recent bootstrap procedures for robust performance testing and data snooping control. Thus, we provide a profound insight to the question whether a

[3] Arnott, Hsu, and Moore (2005) also report an alpha of -0.1% using the same framework.

weighting scheme based on fundamentals or market capitalization is superior, and hence fill an important gap in the literature.

We investigate the concept of fundamentally weighted portfolios with a broad as possible worldwide data sample of 50 developed and emerging countries expanding the focus to a global level, since previous research centered mainly on the U.S. market or European indexes. Therefore, we construct global fundamentally weighted portfolios to examine the performance of the concept in a highly diversified environment and create a domestic fundamentally weighted portfolio for each country in our sample.

Our analysis establishes the following main results. First, we find that all global fundamentally weighted versions and 46 out of 50 country-specific fundamentally weighted portfolios create higher returns than their capitalization-weighted counterparts with similar volatility. Hence, in a mean-variance sense, fundamental indexing should offer more efficient outcomes. This finding is consistent with the results of Arnott, Hsu, and Moore (2005) and Hemminki and Puttonen (2008), and Stotz, Döhnert, and Wanzenried (2007). However, none of these studies has addressed the robustness of their findings. Therefore, we subject our results to the recent bootstrap approach of Ledoit and Wolf (2008) for robust performance testing. We establish that the superior performance of global fundamentally weighted portfolios appears robust, while the superior performance of country-specific fundamentally weighted portfolios diminishes considerably.

Second, we decompose the performance in a single-factor framework, as well as by applying Fama and French's (1993) three-factor model and Carhart's (1997) four-factor model with global and country-specific self-constructed size, value and momentum factors. Our results suggest that fundamental indexes provide economically and statistically significant positive alphas worldwide.

Third, when simultaneously testing several investment strategies against a common benchmark, some strategies could outperform others by chance alone. For instance, extensive re-use of a given database or testing one investment idea on various markets of similar nature are prime examples. The latter case applies to our setting, since we examine the concept of fundamental indexing in a large number of equity markets simultaneously. Therefore, we must combine the individual hypotheses into multiple testing procedures that control for possible data snooping biases. In this context, we apply the approach of Romano and Wolf (2005), who suggest a stepwise multiple testing procedure (StepM) that asymptotically controls the familywise error rate (FWE). After controlling for data snooping biases, there is evidence of outperforming global fundamental indexes, but no compelling evidence of outperforming country-specific fundamental indexes.

The remainder of the paper is organized as follows. In Section 2, we describe the data and explain the construction methodology of our fundamentally weighted portfolios. In Section 3, we analyze the risk and return characteristics of fundamental indexing in a global and country-specific environment. Section 4 then presents and interprets the results of the applied performance attribution models. Finally, Section 5 concludes our findings.

2. Data and portfolio construction methodology

2.1. Data

Using Thomson Financial Datastream, we obtain monthly total return data (that is, including dividends) for all firms listed on the major exchanges of 50 developed and emerging countries from July 1982 to June 2008. To avoid a possible survivorship bias (Brown, Goetzmann, Ibbotson, and Ross (1992)), delisted stocks are included until they disappear. Since we cover companies from different countries with different currencies, all data are converted to U.S. dollars. From this sample, we select those stocks that have at least one fundamental variable such as book value, cash flow, dividends, number of employees, income, and sales available. These company-accounts items are obtained from the Worldscope database. Since Ulbricht and Weiner (2005) find no statistical or methodological shortcomings in Worldscope data for U.S. firms in comparison with COMPUSTAT, we employ Worldscope for all countries. The sample period was selected to encompass a history as long as possible with return data from Datastream, and a coverage of markets as broad as possible. Although Datastream has stock return data extending further back than 1982, the required accounting data from Worldscope are not available before 1980. Since the calculation of the momentum factor requires a return history of at least 12 months, we have to choose 1982 as the earliest possible start date for our study.

In addition to the sampling criteria described above, we apply several screening procedures as suggested by Ince and Porter (2006) for studies involving large numbers of individual equities.[4]

While previous studies limited the constituents of the fundamentally weighted portfolios to a specific number, for example 1,000 stocks (see Arnott, Hsu, and Moore, 2005; Chen, Chen, and Bassett, 2007), or merely re-weighted an existing index according to fundamentals (see Hemminki and Puttonen, 2008; Stotz, Döhnert, and Wanzenried, 2007), the number of firms in our portfolios has been growing steadily.

On the first portfolio construction date, at the end of June 1982, we have data for 2,846 firms available from which portfolios are formed. As of June 2007, the last portfolio rebalancing date, the number of stocks in our sample amounts to 22,658 surviving firms (5,280 firms vanished over the sample period). Table 1 presents further summary statistics for each country in our sample. Most of the developed countries have return data available from the beginning of our sample period, whereas many emerging countries have return data initially available by the beginning of the 1990's. Altogether, our worldwide sample encompasses a total of 300,808 firm-years. The majority of firm-year observations are concentrated in the United States (72,955), Japan (56,805), and the United Kingdom (22,625).

[Please insert **Table 1** about here]

[4] We describe the screening procedures in detail in a Supplementary Appendix available on request.

2.2. Portfolio construction methodology

In the vein of Arnott, Hsu, and Moore (2005), we construct fundamentally weighted portfolios based on book value, cash flow, dividends, employees, income, and sales. Since Boudoukh, Michaely, Richardson, and Roberts (2007) find that the stock return predictability in time-series is much stronger when (net) payout yields are used instead of the dividend yield, we also construct a fundamentally weighted portfolio based on the net payout of the firm. The net payout is defined as the sum of distributed dividends, plus the total expenditures used to decrease the outstanding shares (repurchases), minus the proceeds received from the sale of shares (equity issuance) over the past year. k denotes the single metrics book value *bv*, cash flow *cf*, dividends *div*, employees *emp*, income *in*, net payout *np*, and sales *sal*.

The specific construction of the fundamentally weighted portfolios then proceeds as follows: at the end of June of each year t (1982 - 2007), all firms in the considered sample (global and country-specific) are weighted by its fundamental metric. Each company in the portfolio is assigned a weight according to its relative weight for that metric:

$$w_{k,i,t} = \frac{\max\left[0, F_{k,i,t-1}\right]}{\sum_{j=1}^{N} \max\left[0, F_{k,j,t-1}\right]}, \tag{1}$$

where $F_{k,i,t-1}$ is the metric k of company i at fiscal year-end $t - 1$. It should be emphasized that the metric $F_{k,i,t-1}$ is computed on a total-company basis, but not on a per-share basis. If a fundamental metric is negative, it is set to zero. This approach excludes short positions in stocks.[5]

In addition to the single metrics described above, we also examine a composite portfolio combining the metrics book value, cash flow, dividends, and sales. The weight of a firm in the composite portfolio $\overline{w}_{comp,i,t}$ is calculated as the average of the weights each firm would have in the four individual metrics. Since this approach would attach less weight to all firms that do not distribute dividends, the weight in the composite portfolio for a non-dividend-paying firm is the average of the remaining three fundamental metrics. If the metric book value or cash flow is negative, the composite metric is set to zero, again excluding short positions.

$$\overline{w}_{comp,i,t} = \begin{cases} \frac{1}{4}\sum_{j=1}^{4} w_{j,i,t}, & \forall w_{k,i,t} \in \mathfrak{A} > 0, \mathfrak{A} := \left\{w_{bv,i,t}, w_{cf,i,t}, w_{sal,i,t}, w_{div,i,t}\right\} \\ \frac{1}{3}\sum_{j=1}^{3} w_{j,i,t}, & \forall w_{k,i,t} \in \mathfrak{M} > 0 \wedge w_{div,i,t} = 0, \mathfrak{M} := \left\{w_{bv,i,t}, w_{cf,i,t}, w_{sal,i,t}\right\}, \\ 0, & otherwise \end{cases} \tag{2}$$

Because these four metrics used in the composite portfolio are widely available in most countries, the composite portfolio can be easily applied in an international environment. Moreover, the composite approach is expected to result in weights that reflect the fair value of a firm in a robust way, because possible valuation biases of a single metric are more likely to be offset. We do not argue that it is the most efficient metric.

[5] Note that our results are not driven by imposing short sale constraints in the weighting mechanism. Without these, our results (not reported) do not change in a material way.

To ensure that the accounting data for all fiscal year-ends in calendar year t – 1 are known before the returns are calculated, the fundamentally weighted portfolio is rebalanced at the end of June of each year. In this way, we avoid a possible look-ahead bias. The composition is then held constant over one year and the returns for the portfolio are calculated from July of year t to June of t + 1. For benchmarking purposes, we also create capitalization-weighted reference portfolios (global and country-specific) by using the same construction method with the only distinction that the metric $F_{k,i,t-1}$ now represents the total equity market capitalization of company i at fiscal year-end t – 1. Thus, any comparison between the two weighting schemes is not distorted by using different data and construction methods.

3. Risk and return analysis

In this section, we analyze the risk and return characteristics of global and country-specific fundamentally weighted portfolios, to obtain a first assessment of their performance. In this context, we also apply a recent bootstrap procedure for robust performance testing.

3.1. Global fundamentally weighted portfolios

Table 2 shows the risk and return characteristics for our global fundamentally weighted portfolios and their capitalization-weighted benchmark (reference portfolio) for the 26-year period from July 1982 to June 2008.

[Please insert **Table 2** about here]

The highest ending value for a $ 1 investment made at the beginning of our sample period is reached by the net payout-weighted portfolio. The book value-weighted portfolio generates the smallest ending value which is, however, higher than the capitalization-weighted reference portfolio. The annualized volatility of returns suggests that higher returns cannot be attributed to higher risk.

The annualized Sharpe ratio, which measures the excess return over the risk-free rate per unit of overall risk, yields a value of 0.473 for the reference portfolio over the sample period. All global fundamental indexes, however, display considerably higher values for the Sharpe ratio.

Although Sharpe ratios of the fundamental indexes appear higher in absolute magnitude, these results could be spurious and do not necessarily indicate superior performance on a risk-adjusted basis. Therefore, we will subject the difference of the Sharpe ratios of the two weighting schemes to a recent econometric method. The current approach in the applied literature seems to be the parametric test of Jobson and Korkie (1981) as used by Amenc, Goltz, and Le Sourd (2009). Memmel (2003) corrects a typographical error in the original proposal. However, this test is not robust against tails heavier than the normal distribution and time series characteristics (non i.i.d. returns). Since both effects are quite common with financial return data, we apply instead the approach of Ledoit and Wolf (2008) for robust performance testing as follows. We test the null hypothesis of equality of the Sharpe ratios of the considered fundamentally weighted portfolio and the capitalization-weighted reference portfolio (H_0: $\Delta = 0$). For this, we construct a studentized time series bootstrap confidence interval with nominal level $1 - \alpha$ for the difference Δ. If this interval does not contain zero, then H_0 is rejected at nominal level α and we declare the two ratios different. We employ the circular blocks bootstrap of Politis and Romano (1992). The bootstrap procedure uses a data-dependent choice of block size based on the calibration function of Loh (1987). The nominal levels considered are 0.01, 0.05, and 0.10. All bootstrap p-values are computed employing 5,000 resamples.

In Column 7 (*Δ Sharpe Ratio*), the difference of the Sharpe ratios is presented for each fundamentally weighted portfolio with the corresponding statistical significance computed by the bootstrap procedure. The results lead to a rejection of the null. All global fundamental indexes exhibit highly significant and positive differences, indicating a superior performance on a risk-adjusted basis, compared to the reference portfolio.

We also measure the concentration of a portfolio towards large-capitalization stocks. Therefore, we examine the fraction of the total market capitalization that belongs to the 100 highest ranked stocks in each portfolio. Over the whole sample period, the lowest concentration in large stocks is exposed by the employees-weighted portfolio with a ratio of 25.5%; the dividend-weighted portfolio exhibits the highest value with 40.5%, which is nearly identical to the reference portfolio's fraction of 41.1%.

To draw a first conclusion based on the descriptive and bootstrapped results above, our global fundamentally weighted portfolios are superior in comparison to the capitalization-weighted reference portfolios regarding their risk and return characteristics.

3.2. Country-specific fundamentally weighted portfolios

After the initial analysis of the global portfolios, we take a closer look at the country-specific versions, which draw a more heterogeneous picture. Table 3 provides the arithmetic return per annum, the annualized volatility and the Sharpe ratio for the composite fundamentally weighted portfolio and the capitalization-weighted reference portfolio for each country. The Sharpe ratio difference with the corresponding significance level between the considered fundamental index and its capitalization-weighted counterpart are reported as well.

[Please insert **Table 3** about here]

Only four out of the 50 domestic fundamental indexes exhibit a negative return difference relative to their traditional market indexes, namely Morocco, Colombia, Venezuela and Taiwan. Comparing the standard deviation of returns, we find that 25 out of the 50 fundamental indexes produce an annualized volatility that is lower than that of their corresponding traditional market portfolio. With the exception of Russia, which exhibits an additional volatility of 19.20% per year, the remaining fundamentally weighted portfolios show only a slightly higher volatility relative to their benchmarks.

From the 46 positive Sharpe ratios, 43 fundamentally weighted portfolios outperform their capitalization-weighted counterparts on a risk-adjusted basis. However, when we test the null hypothesis of equality of the Sharpe ratios of the considered domestic fundamental index and its capitalization-weighted counterpart by applying the bootstrap method of Ledoit and Wolf (2008), the superior performance diminishes to 14 countries with positive different Sharpe ratios significant on a 5% level or better. The majority of the countries with significant positive differences are developed countries (11 of 28 developed countries vs. 3 of 22 emerging markets in our sample according to the International Monetary Fund (IMF) classification), where markets are assumed to be most efficient. However, whereas the superiority of fundamental indexing for the U.S. market reported by Arnott, Hsu, and Moore (2005) can be replicated for the descriptive Sharpe ratio, the difference turns out not to be statistically significant applying the bootstrap methodology.

4. Performance attribution

4.1. Methodology

Having analyzed the risk and return characteristics of fundamental indexes in a global and country-specific context, we will now decompose the performance in a single- and multi-factor framework. The three performance attribution models we use in this study are the classical CAPM established by Sharpe (1964), Lintner (1965), and

Mossin (1966), the three-factor model by Fama and French (1993), and the four-factor model by Carhart (1997). These models are estimated from the following regressions:

$$r_{i,\tau} - r_{f,\tau} = a_i + b_i(r_{m,\tau} - r_{f,\tau}) + \varepsilon_{i,\tau} \tag{3}$$

$$r_{i,\tau} - r_{f,\tau} = a_i + b_i(r_{m,\tau} - r_{f,\tau}) + s_i SMB_\tau + h_i HML_\tau + \varepsilon_{i,\tau} \tag{4}$$

$$r_{i,\tau} - r_{f,\tau} = a_i + b_i(r_{m,\tau} - r_{f,\tau}) + s_i SMB_\tau + h_i HML_\tau + w_i WML_\tau + \varepsilon_{i,\tau} \tag{5}$$

Where $r_{i,\tau}$ is the return on fundamentally weighted portfolio i in month τ, $r_{f,\tau}$ is the one-month Treasury bill rate in month τ, and $r_{m,\tau}$ is the return on the capitalization-weighted market portfolio in month τ. SMB, HML and WML are designed to capture common non-market risk factors that are related to size, book-to-market ratio and momentum. Finally, the factor loadings are respectively b_i, s_i, h_i, and w_i.

The starting point for our performance attribution is the classical CAPM where the intercept of the regression, commonly labeled as Jensen's alpha (1968) is usually interpreted as a measure of out- or underperformance relative to the market proxy used. However, subsequent research shows empirical contradictions and anomalies that strongly question the validity of the CAPM (Banz (1981), Fama and French (1992)). As a consequence, the CAPM is extended by Fama and French (1993) to a multi-factor model with mimicking portfolios for the size and value effect as explanatory variables. At the same time, Jegadeesh and Titman (1993) find a significant one-year momentum anomaly for the U.S. stock market by showing a positive return differential for portfolios formed of past winner and loser stocks. Since this momentum effect cannot be explained by the Fama and French (1993) model, Carhart (1997) proposes an extension by adding a mimicking portfolio for the momentum anomaly to the three-factor-model.

Because country-specific risk factors apart from the U.S. are not readily available, we construct domestic risk factors for each country in our sample, as well as global versions for the performance attribution of our global fundamentally weighted portfolios.[6] Since the findings of Griffin (2002) show that the Fama and French factors are country-specific, the application of international size and value factors to individual countries leads to disappointing results in relation to the explanatory power of time-series variation. Since the same is true for the momentum factor, national and global versions are formed as well.

4.2. Multiple testing

When simultaneously testing several investment strategies against a common benchmark, some strategies could outperform others by chance alone. For instance, extensive re-use of a given database or testing one investment idea on various markets of similar nature are prime examples. Especially, the latter case applies to our setting, since we examine the concept of fundamentally weighted portfolios in a large number of equity markets simultaneously. Therefore, we must combine the individual

[6] We describe the construction in more detail in the Appendix.

hypotheses into multiple test procedures that control for possible data snooping biases.

In this context, we apply the approach of Romano and Wolf (2005), who suggest a stepwise multiple testing procedure (StepM) that asymptotically controls the familywise error rate (FWE) to identify those countries where the fundamental weighting scheme actually outperforms the traditional capitalization weighting.

The most familiar multiple testing method for controlling the FWE is the Bonferroni (1936) method, which consists of a simple p-value adjustment: specifically, the initial significance level α is divided by the number of hypotheses under test. The disadvantage of this method is, in general, its conservatism, which can result in low power. However, it is important to use a method that provides as much power as possible so that false hypotheses have a chance of being rejected.

The method of Romano and Wolf (2005) has the following two main advantages. First, it improves upon Bonferroni-type methods based on the individual p-values by incorporating the dependence structure across test statistics. Second, it improves upon the bootstrap reality check of White (2000) by incorporating a stepwise approach.

The StepM method relabels all strategies under consideration in descending order of their test statistics, from largest to smallest. Then, a joint bootstrap confidence region is determined with coverage probability $1 - \alpha$. If a particular confidence interval does not contain zero, the corresponding null hypothesis is rejected and a new joint confidence region is determined for the remaining strategies. This stepwise process is then repeated until no further hypotheses are rejected. Such a stepwise procedure is more powerful than a single-step method, but still asymptotically controls the FWE at level α.

We consider the individual testing problem of the following form, each referring to the fundamentally weighted portfolio *s*:

$$H_s : \theta_s \leq 0 \; versus \; H'_s : \theta_s > 0.$$

The parameter of interest here is $\theta_s = \alpha_s$ according to the single- or multi-framework alpha. We define the parameter θ_s in such a way that under the null hypothesis H_s, the specific fundamental index *s* does not beat the zero benchmark. The test statistic for the alpha is respectively the intercept from the corresponding regression of the performance attribution model, studentized by the estimated standard deviation of the test statistic using the Parzen kernel, see Andrews (1991). We perform the multiple testing at a significance level of 5%. The bootstrap method is the stationary bootstrap of Politis and Romano (1994).

Thus, we additionally test the null hypothesis that the considered fundamental index does not beat the zero benchmark. The Rej.-value equals 1 if zero is not included in the particular confidence region, obtained by the StepM method, which indicates the rejection of the null hypothesis and suggests that the fundamental weighting scheme actually outperforms capitalization weighting.[7]

[7] We additionally employ six more traditional multiple testing procedures to put our following results for the CAPM and the multi-factor models obtained with the StepM method in perspective. These

4.3. Results of the CAPM

In the following two subsections, we will discuss the main conclusions that can be drawn from the results of the single-factor model. All estimations are based on Newey-West (1987) standard errors to adjust for autocorrelation and heteroskedasticity in the returns.

4.3.1. Results for the global fundamentally weighted portfolios

Table 4 presents the results applying the classical CAPM for the global fundamentally weighted portfolios. Column two reports the CAPM alpha a and Column three the beta coefficient b.[8]

[Please insert **Table 4** about here]

The results from the single-factor model show that the monthly alphas generated by all global fundamental indexes are highly significant and positive. These results are also robust with respect to data snooping. The beta coefficients, which measure the systematic risk of the fundamentally weighted portfolios relative to the market portfolio, are all below one. Particularly, the dividends-weighted portfolio has the

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procedures are based on Bonferroni (1936), Holm (1979), Hochberg (1988), Hommel (1988), Benjamini and Hochberg (1995), and Benjamini and Yekutieli (2001). The results shown in a Supplementary Appendix (available on request) are consistent with our main results.

[8] The magnitude of R^2 in the following tables is typical for this literature. See, e.g., Jun and Malkiel (2008), or Amenc, Goltz, and Le Sourd (2009).

smallest beta coefficient with a value of 0.80, whereas the sales-weighted portfolio exhibits with 0.96 the highest beta factor. Thus, single-factor results suggest that fundamental weighting in a global context is superior to capitalization weighting generating a positive Jensen's alpha with less exposure to the market risk.

4.3.2. Results for the country-specific fundamentally weighted portfolios

Considering the regression results of the CAPM for the country-specific portfolios, as reported in Table 5, we receive a much more heterogeneous picture.

[Please insert **Table 5** about here]

14 of the 50 national fundamentally weighted portfolios have an alpha that is significantly different from zero on a 5% level or better. We observe that the statistically significant fundamental indexes are also promising in terms of economic significance. Testing the robustness of the results, the StepM method yields seven rejections for the CAPM alphas. The market exposure designated by the beta coefficient is on average similar to that of the global fundamental indexes, but with a higher grade of dispersion.

4.4. Multi-factor models

We apply multi-factor models for a further performance attribution. This endeavor is especially interesting, since opponents of the fundamental weighting concept argue that the excellent performance does not stem from their superior weighting scheme, but is rather due to their augmented exposure to value and small-capitalization stocks (see Jun and Malkiel, 2008).

4.4.1 Results for the global fundamentally weighted portfolios

Table 6 presents the regression results for the global fundamental indexes applying the four-factor model of Carhart (1997).[9]

[Please insert **Table 6** about here]

The loadings on the value factor (HML factor) are positive for all portfolios and highly significant. The exposure to the value premium ranges from 0.19 (sales) to 0.33 (employees), indicating that the returns of fundamentally weighted portfolios are mainly driven by stocks with high book values relative to their market values. The loadings on the size factor (SMB factor) are positive, but only for three out of eight portfolios significant at the 5% level or better. The magnitude of the exposure to the size factor is considerably lower in comparison to the value factor, ranging only from 0.02 (sales) to 0.09 (employees). The loadings on the momentum factor (WML factor) are positive for all but one, however for none of the global portfolios statistically significant different from zero. After adjustment for the inherent value and size tilts in the returns, five out of eight global fundamental indexes still exhibit

[9] We also performed all calculations using the three-factor model of Fama and French (1993) obtaining results very similar to those of the Carhart (1997) model. For the sake of brevity, we do not report them here.

a significant positive alpha at the 5% level or better. Testing the robustness of these results, the StepM method yields four rejections, namely cash flow, dividends, income, and the composite version. As a further robustness test, we obtain qualitatively similar results (tables not reported) when rerunning the regressions with a novel fundamentally weighted Carhart-model based on book value instead of employing the usual capitalization-weighted components in the mimicking portfolios.

If fundamental weighting solely provided a means to a simple value strategy, one would not expect to observe economically and statistically significant positive alphas in the multi-factor framework. It is therefore safe to say that fundamental weighting delivers more than just a value strategy based on sorting stocks into quintile or decile portfolios. Also, the fundamentally weighted portfolio based on the composite metric combining the metrics book value, cash flow, dividends, and sales belongs to the group of outperforming metrics.

4.4.2. Results for the country-specific fundamentally weighted portfolios

Across all countries, the results of the performance attribution using the four-factor model are reported in Table 7.[10]

[Please insert **Table 7** about here]

[10] Because of the low number of stocks, unfortunately, we cannot calculate adequate factor portfolios for the following five countries: Colombia, Venezuela, Sri Lanka, Czech Republic, and Estonia. Due to this fact, we have to exclude these markets from our further analysis.

We identify 19 out of 45 domestic fundamental indexes that have significant positive alphas on a 5% level or better. The magnitude ranges here from 14 basis points (United Kingdom) to 56 basis points (India). In comparison to the single-factor model, five additional countries now exhibit a positive alpha that is significant at the 5% level or better. These countries are the USA, India, Israel, Thailand, and the United Kingdom. 15 of these 19 markets belong to developed countries (total sample: 28 developed and 22 emerging countries, based on the IMF classification). The suggestion of Hsu, Li, Myers and Zhu (2007) that fundamental indexes have the greatest advantage in emerging countries, where markets are presumably the least efficient, is somewhat contrasted by our results.

We next consider the economic importance of the outperforming fundamentally weighted portfolios measured in terms of their market value contribution to the world market portfolio or their absolute fundamental metric contribution to the absolute world fundamental metric. Fig. 1 displays that the respective countries are heavy weights responsible for nearly 90% of the world market for both definitions.

[Please insert **Fig. 1** about here]

The heavy weight of the outperforming domestic fundamentally weighted portfolios explains why global fundamental weighting works. Alternative explanations as diversification potential, market timing ability, or sector allocation add only little to our understanding of this result.[11]

[11] Results are reported in a Supplementary Appendix (available on request).

However, some alphas could be spurious, since they arise from single hypothesis tests performed for each country. Still, six portfolios prevail after subjecting the alphas to the Romano and Wolf (2005)-multiple hypotheses test. We identify the same countries within the single-factor framework, only excluding Italy.[12] An arbitrary investor selecting a specific domestic fundamental index (e.g., due to home bias) is likely not to outperform the respective capitalization-weighted index because only six of 45 country-specific indexes achieve this.

Again, the results indicate that part of the risk-adjusted returns exhibits a positive alpha and can be attributed to the value factor, and to a lesser extent, the size and momentum factor. The exposure to the value premium is significantly positive for 32 fundamental indexes at the 5% level or better and ranges here from 0.03 (Morocco) to 0.25 (Finland). The loading on the size factor – significant for 13 fundamental indexes – reveals mixed results, with some exposures positive and most negative. As shown in the prior subsection, the momentum factor also plays only a minor role in explaining the return behavior of the domestic fundamentally weighted portfolios. Russia is an exception for which the exposure with 0.48 is significant.

5. Conclusion

This paper explores the concept of fundamental indexing around the world. Using an international sample of 50 developed and emerging countries, we provide in-

[12] As a further robustness test, we again obtain qualitatively similar results (tables not reported) when rerunning the regressions with a novel fundamentally weighted Carhart-model based on book value.

sight into the return behavior of fundamentally weighted portfolios on a global and country-specific level. In this way, we expand the focus to a global level, since previous studies centered mainly on the U.S. or Europe.

First, we establish that superior performance of domestic fundamentally weighted portfolios diminishes considerably when applying a bootstrap procedure by Ledoit and Wolf (2008) for robust performance testing. Second, we decompose the performance in a multi-factor framework. We account for data snooping biases using the Romano and Wolf (2005)-StepM method. The assessment that fundamental indexing is nothing but a simple value strategy seems utterly harsh in light of our results. Even after controlling for data snooping biases in multiple ways, and the value premium within the Carhart (1997) four-factor model, we find evidence that fundamental indexing produces economically and statistically significant positive alphas. This holds for the global and the country-specific fundamental index versions which are heavily weighted in the world capital market portfolio according to their specific fundamental metric or their market value. These findings have important implications for event studies or performance-evaluation because fundamentally weighted portfolios pose a serious alternative to capitalization-weighted portfolios in this context. However, an arbitrarily selected domestic fundamental index is not likely to beat the respective capitalization-weighted index because only six of 45 country-specific fundamental indexes achieve such an outperformance.

Appendix: Construction of the SMB, HML, and WML factors

For the construction of the SMB and HML factor in each country, we follow the methodology of Fama and French (1993) with the only peculiar exception of not using NSYE breakpoints. Specifically, at the end of June of each year t (1982 - 2007), stocks are allocated to two groups small or big (S or B) based on whether their June market equity, ME (stock price times shares outstanding), is below or above the median for all stocks in the considered sample.

Similarly, stocks are allocated in an independent sort to three book-to-market equity (BE/ME) groups based on the breakpoints for the bottom 30 percent (L), middle 40 percent (M), and top 30 percent (H) of the ranked values of book-to-market for the stocks in the considered sample. The book-to-market ratio used to form portfolios in June of year t is calculated as the book equity for the end of calendar year t – 1, divided by market equity at the end of December of t – 1. We do not use firms with negative book equity when calculating the breakpoints for our portfolios.

The six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) are then formed from the intersections of the two size and the three book-to-market equity groups. Monthly capitalization-weighted and fundamentally weighted returns on the six portfolios are calculated from July of year t to June of t + 1, and the portfolios are reformed at the end of June of t + 1. We calculate returns beginning in July of year t to be sure that book equity for year t – 1 is known. To be included in the portfolios formed in June of year t, firms must have stock prices for December of year t – 1 and June of year t, and book equity for year t – 1.

The SMB (small minus big) portfolio, meant to mimic the risk factor in returns related to size, is the difference, each month, between the simple average of the returns on the three small-stocks portfolios and the simple average of the returns on the three big-stock portfolios, calculated as follows: (S/L + S/M + S/H)/3 – (B/L + B/M + B/H)/3.

The HML (high minus low) portfolio, meant to mimic the risk factor in returns related to book-to-market equity, is similarly defined. HML is the difference, each month, between the simple average of the returns on the two high book-to-market equity portfolios and the average of the returns on the two low book-to-market equity portfolios, calculated as follows: (S/H + B/H)/2 – (S/L + B/L)/2.

The approach chosen for the construction of the momentum factor WML is related to Carhart (1997) and Jegadeesh and Titman (1993). Specifically, at the end of each month, all stocks in the considered sample with a return history of at least 12 months are allocated to three momentum portfolios based on the breakpoints for the bottom 30 percent (Losers), middle 40 percent (Neutral), and top 30 percent (Winners) of their prior 12-month performance.

These portfolios are then held for 12 subsequent months and monthly capitalization-weighted and fundamentally weighted returns are calculated for each.

The WML (winners minus losers) portfolio, meant to mimic the risk factor in returns related to momentum, is then the difference, each month, between returns on the winner stock portfolio and the returns on the loser stock portfolio, calculated as follows: Winners – Losers.

To increase the power of the momentum effect, the winners (losers) portfolio is constructed as an overlapping portfolio, as suggested by Jegadeesh and Titman (1993). Therefore, in any given month τ, the final winners (losers) portfolio consists of the portfolio formed in the current month , as well as the portfolios formed in $\tau - 1$, $\tau - 2$, and so on up to $\tau - 11$. This approach is equivalent to a composite portfolio in which each month 1/12 of the holdings are revised. Thus, the return of the winners (losers) portfolio in τ is respectively the average of 12 portfolio returns.

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Table 1
Number of stocks and firm years: 1982-2007
This table reports summary statistics for all countries in our sample, sorted by region. The start year of returns (beginning in the month of July) indicates the inclusion of that country in our sample. That is, when a return history of at least 12 months is available. The number of stocks is the total number of unique stocks in our sample as of June 2007, the last portfolio rebalancing date. The last two columns show the number of firm years available for that country, and its proportion in the complete sample.

Country	Start Year of Returns	Number of Stocks	Firm Years	Portion	Country	Start Year of Returns	Number of Stocks	Firm Years	Portion
Africa					Europe				
Egypt	1999	50	380	0.13%	Austria	1986	81	1,253	0.42%
Morocco	2001	24	161	0.05%	Belgium	1982	135	2,064	0.69%
South Africa	1984	244	3,592	1.19%	Czech Republic	1997	16	268	0.09%
America					Denmark	1982	161	3,072	1.02%
Argentina	1994	61	793	0.26%	Estonia	2005	7	15	0.00%
Brazil	1999	88	563	0.19%	Finland	1989	125	1,582	0.53%
Canada	1982	1,167	16,712	5.56%	France	1982	802	10,197	3.39%
Chile	1992	134	1,934	0.64%	Germany	1982	949	12,089	4.02%
Colombia	2005	12	31	0.01%	Greece	1990	262	3,380	1.12%
Mexico	1994	98	1,163	0.39%	Hungary	1997	30	325	0.11%
Peru	1999	55	424	0.14%	Ireland	1987	49	803	0.27%
USA	1982	4,589	72,955	24.25%	Italy	1982	267	3,513	1.17%
Venezuela	1994	16	255	0.08%	Luxembourg	1998	24	229	0.08%
Asia					Netherlands	1986	134	2,613	0.87%
China	2001	136	668	0.22%	Norway	1988	177	1,991	0.66%
Hong Kong	1987	606	6,301	2.09%	Poland	1997	218	1,443	0.48%
India	1992	872	10,262	3.41%	Portugal	1990	51	1,017	0.34%
Israel	1994	94	1,089	0.36%	Russia	1998	90	476	0.16%
Japan	1982	3,665	56,805	18.88%	Spain	1989	130	2,013	0.67%
Malaysia	1989	810	10,150	3.37%	Sweden	1986	284	3,358	1.12%
Pakistan	1994	113	1,207	0.40%	Switzerland	1982	236	4,047	1.35%
Philippines	1999	79	429	0.14%	UK	1982	1,693	22,625	7.52%
Singapore	1988	560	4,627	1.54%	Oceania				
South Korea	1994	685	6,104	2.03%	Australia	1982	1213	11,062	3.68%
Sri Lanka	1999	18	157	0.05%	New Zealand	1993	117	1,087	0.36%
Taiwan	1994	678	7,072	2.35%					
Thailand	1990	332	4,217	1.40%					
Turkey	1997	221	2,235	0.74%	Total		22,658	300,808	100.00%

Table 2
Risk and return characteristics of global fundamentally weighted portfolios
This table shows the risk and return characteristics of the global portfolios from July 1982 to June 2008. The composite metric combines book value, cash flow, dividends, and sales. The first column reports the ending value for a \$ 1 investment made at the beginning of the sample period in that portfolio. The average return is the annualized arithmetic return, and the volatility is annualized. The risk premium of the Sharpe ratio is measured as the excess return over the one-month US Treasury bill rate. The bootstrap method of Ledoit and Wolf (2008) is applied to test the null hypothesis of equality of the Sharpe ratios of the considered fundamentally weighted portfolio and the reference portfolio. The difference of the Sharpe ratios (Δ Sharpe Ratio) and the corresponding statistical significance is reported, where *, **, and *** mean significant at the 10%, 5%, 1% level, respectively. Concentration of a portfolio in large-capitalization stocks is measured by the fraction of the total market capitalization that belongs to the 100 highest ranked stocks in that portfolio. The last column reports the return correlation of that portfolio with the capitalization-weighted reference portfolio.

Portfolio	Ending Value of \$1	Avg. Return	Volatility	Sharpe Ratio	Δ Sharpe Ratio	Concentration	Correlation
Book Value	29.74	14.07%	13.74%	0.655	0.182***	32.6%	0.97
Cash Flow	38.50	15.02%	13.31%	0.746	0.273***	38.5%	0.95
Dividends	36.87	14.75%	12.55%	0.771	0.298***	40.5%	0.92
Employees	38.92	15.08%	14.03%	0.733	0.260***	25.5%	0.93
Income	37.87	14.94%	13.21%	0.747	0.274***	39.0%	0.95
Net Payout	40.89	15.36%	13.54%	0.740	0.267***	37.3%	0.89
Sales	33.81	14.57%	14.31%	0.669	0.196***	28.9%	0.97
Composite	34.53	14.65%	13.17%	0.721	0.248***	36.2%	0.96
Reference	16.57	11.89%	14.42%	0.473		41.1%	

Table 3
Risk and return characteristics of country-specific fundamentally weighted portfolios
This table shows the risk and return characteristics of the country-specific composite portfolios and their capitalization-weighted reference portfolios. The composite metric combines the metrics book value, cash flow, dividends, and sales. The time period under review for each country ranges from the inception of returns for that country (see Table 1) to June 2008. The average return is the annualized arithmetic return, and the volatility is annualized. The risk premium of the Sharpe ratio is measured as the excess return over the one-month US Treasury bill rate. The bootstrap method of Ledoit and Wolf (2008) is applied to test the null hypothesis of equality of the Sharpe ratios of the considered fundamentally weighted portfolio and the reference portfolio. The difference of the Sharpe ratios (Δ Sharpe Ratio) and the corresponding statistical significance is reported, where *, **, and *** mean significant at the 10%, 5%, 1% level, respectively.

Country	Fundamentally Weighted Portfolio			Reference Portfolio			Δ Sharpe Ratio
	Avg. Return	Volatility	Sharpe Ratio	Avg. Return	Volatility	Sharpe Ratio	
				Africa			
Egypt	21.32%	24.95%	0.773	15.57%	26.43%	0.557	0.216
Morocco	28.43%	19.48%	1.256	29.60%	18.77%	1.346	-0.090
South Africa	10.65%	26.10%	0.342	8.84%	26.08%	0.279	0.063
				America			
Argentina	-5.92%	35.15%	[Neg.]	-6.57%	35.37%	[Neg.]	[NA]
Brazil	29.92%	37.05%	0.812	29.61%	36.48%	0.810	0.002
Canada	16.62%	15.73%	0.740	13.21%	17.39%	0.513	0.227**
Chile	13.03%	24.10%	0.472	11.78%	21.51%	0.450	0.022
Colombia	31.23%	30.26%	0.227	36.38%	28.84%	0.425	-0.198
Mexico	9.65%	30.86%	0.340	5.23%	30.01%	0.204	0.136
Peru	19.62%	24.17%	0.732	17.10%	25.83%	0.652	0.080
USA	13.70%	13.76%	0.639	12.55%	14.73%	0.536	0.103
Venezuela	-0.21%	53.58%	0.185	3.04%	48.01%	0.221	-0.036
				Asia			
China	13.08%	33.79%	0.525	6.55%	35.42%	0.235	0.290
Hong Kong	13.88%	28.86%	0.449	12.30%	28.51%	0.400	0.049
India	9.96%	31.76%	0.340	5.61%	30.34%	0.208	0.132
Israel	13.72%	23.79%	0.500	10.79%	24.75%	0.386	0.114
Japan	9.44%	21.80%	0.289	6.88%	22.21%	0.181	0.108**
Malaysia	3.66%	28.30%	0.123	1.15%	29.72%	0.049	0.074**
Pakistan	5.14%	30.78%	0.192	2.70%	32.35%	0.045	0.147
Philippines	-1.79%	30.03%	[Neg.]	-4.37%	33.31%	[Neg.]	[NA]
Singapore	13.20%	23.17%	0.465	9.46%	22.09%	0.324	0.141**
South Korea	17.75%	48.87%	0.470	11.75%	45.63%	0.367	0.103*
Sri Lanka	0.89%	27.06%	0.031	-0.65%	24.79%	[Neg.]	[NA]
Taiwan	-2.07%	26.68%	[Neg.]	-1.76%	28.83%	[Neg.]	[NA]
Thailand	7.33%	37.05%	0.268	-0.75%	34.53%	0.040	0.228**
Turkey	9.71%	57.53%	0.381	7.87%	56.59%	0.344	0.037

Table 3 (*continued)*

Country	Fundamentally Weighted Portfolio			Reference Portfolio			Δ Sharpe Ratio
	Avg. Return	Volatility	Sharpe Ratio	Avg. Return	Volatility	Sharpe Ratio	
Europe							
Austria	15.15%	19.68%	0.593	11.25%	20.25%	0.409	0.184***
Belgium	16.76%	18.97%	0.649	15.42%	18.26%	0.603	0.046
Czech Republic	21.74%	25.84%	0.760	21.43%	29.19%	0.696	0.064
Denmark	15.31%	17.80%	0.608	14.63%	17.79%	0.575	0.033
Estonia	12.69%	18.17%	0.545	7.63%	20.55%	0.268	0.277
Finland	13.68%	22.61%	0.497	10.80%	29.21%	0.354	0.143
France	18.55%	19.92%	0.704	15.70%	19.47%	0.590	0.114**
Germany	14.73%	19.26%	0.551	11.76%	19.72%	0.408	0.143***
Greece	8.37%	28.29%	0.284	3.52%	28.49%	0.124	0.16**
Hungary	20.81%	31.42%	0.657	16.45%	30.69%	0.548	0.109
Ireland	16.11%	21.47%	0.613	14.15%	22.30%	0.513	0.100
Italy	14.29%	24.37%	0.461	10.79%	23.38%	0.337	0.124***
Luxembourg	8.65%	23.23%	0.333	5.92%	26.41%	0.232	0.101
Netherlands	13.64%	18.10%	0.556	12.17%	17.04%	0.501	0.055
Norway	16.03%	23.45%	0.570	14.61%	22.91%	0.524	0.046
Poland	17.00%	31.31%	0.550	10.78%	32.02%	0.374	0.176**
Portugal	10.16%	19.55%	0.392	5.40%	20.01%	0.165	0.227***
Russia	27.26%	66.02%	0.658	24.37%	46.82%	0.629	0.029
Spain	14.40%	19.66%	0.574	11.24%	19.81%	0.429	0.145***
Sweden	14.26%	23.57%	0.497	12.37%	26.22%	0.408	0.089
Switzerland	15.19%	17.85%	0.601	14.45%	16.68%	0.593	0.008
United Kingdom	14.53%	17.22%	0.583	12.79%	16.75%	0.502	0.081
Oceania							
Australia	16.17%	21.32%	0.580	13.44%	21.25%	0.469	0.111***
New Zealand	9.70%	21.71%	0.360	9.23%	22.10%	0.339	0.021

Table 4
Performance measurement for global fundamentally weighted portfolios using the CAPM
This table presents the regression results from applying the CAPM for explaining the monthly excess returns of the global portfolios from July 1982 to June 2008. All the estimates are obtained by OLS. Newey-West robust standard errors are used. The regression R^2 is adjusted for degrees of freedom. *, **, and *** mean significant at the 10%, 5%, 1% level, respectively. The last column Rej. denotes the result of the multiple testing procedure as obtained by the Romano and Wolf (2005)-StepM method. Under test is respectively the null hypothesis that the considered fundamentally weighted portfolio does not beat the zero benchmark (H_0: a = 0). Rej. equaling 1 indicates the rejection of the null hypothesis, which suggests that the considered fundamentally weighted portfolio actually outperforms the traditional benchmark.

Portfolio	a	b	R^2	Rej.
Book Value	0.22%***	0.93***	0.95	1
Cash Flow	0.32%***	0.88***	0.91	1
Dividends	0.35%***	0.80***	0.85	1
Employees	0.34%***	0.90***	0.86	1
Income	0.33%***	0.87***	0.91	1
Net Payout	0.36%***	0.83***	0.79	1
Sales	0.25%***	0.96***	0.94	1
Composite	0.30%***	0.87***	0.91	1

Table 5
Performance measurement for country-specific fundamentally weighted portfolios using the CAPM

This table presents the regression results from applying the CAPM for explaining the monthly excess returns of the country-specific composite portfolios. The time period under review for each country ranges from the inception of returns for that country (see Table 1) to June 2008. All the estimates are obtained by OLS. Newey-West robust standard errors are used. The regression R^2 is adjusted for degrees of freedom. *, **, and *** mean significant at the 10%, 5%, 1% level, respectively. Columns Rej. denote the result of the multiple testing procedure as obtained by the Romano and Wolf (2005)-StepM method. Under test is respectively the null hypothesis that the considered fundamentally weighted portfolio does not beat the zero benchmark (H_0: a = 0). Rej. equaling 1 indicates the rejection of the null hypothesis, which suggests that the considered fundamentally weighted portfolio actually outperforms the traditional benchmark.

Country	a	b	R^2	Rej.
Africa				
Egypt	0.52%*	0.89***	0.89	0
Morocco	-0.13%	1.03***	0.98	0
South Africa	0.13%	1.00***	0.96	0
America				
Argentina	0.13%	0.96***	0.94	0
Brazil	0.23%	0.93***	0.83	0
Canada	0.33%***	0.86***	0.90	1
Chile	0.10%	1.06***	0.94	0
Colombia	-0.48%*	1.03***	0.97	0
Mexico	0.39%	0.98***	0.91	0
Peru	0.27%	1.01***	0.88	0
USA	0.15%	0.89***	0.91	0
Venezuela	-0.10%	1.05***	0.89	0
Asia				
China	0.48%	0.94***	0.93	0
Hong Kong	0.13%	0.99***	0.97	0
India	0.39%	0.97***	0.85	0
Israel	0.33%*	0.88***	0.85	0
Japan	0.21%**	0.95***	0.95	0
Malaysia	0.18%**	0.94***	0.98	0
Pakistan	0.23%	1.01***	0.94	0
Philippines	0.22%	0.80***	0.87	0
Singapore	0.29%***	1.02***	0.94	0
South Korea	0.50%**	1.05***	0.93	0
Sri Lanka	0.19%	1.01***	0.93	0
Taiwan	-0.04%	0.82***	0.86	0
Thailand	0.67%*	1.01***	0.85	0
Turkey	0.21%	1.00***	0.96	0

Country	a	b	R^2	Rej.
Europe				
Austria	0.32%***	0.95***	0.95	1
Belgium	0.09%	1.02***	0.96	0
Czech Republic	0.52%	0.66***	0.55	0
Denmark	0.11%	0.93***	0.86	0
Estonia	0.44%	0.83***	0.88	0
Finland	0.34%	0.69***	0.80	0
France	0.23%***	0.98***	0.92	0
Germany	0.24%***	0.96***	0.97	1
Greece	0.39%***	0.96***	0.93	0
Hungary	0.47%	1.01***	0.97	0
Ireland	0.24%	0.89***	0.86	0
Italy	0.27%***	1.02***	0.95	1
Luxembourg	0.22%	0.83***	0.89	0
Netherlands	0.12%	1.01***	0.90	0
Norway	0.15%	0.96***	0.88	0
Poland	0.49%**	0.95***	0.94	0
Portugal	0.37%***	0.96***	0.92	1
Russia	0.36%	1.13***	0.61	0
Spain	0.25%***	0.98***	0.98	1
Sweden	0.20%	0.85***	0.90	0
Switzerland	0.04%	1.04***	0.94	0
UK	0.13%*	1.01***	0.96	0
Oceania				
Australia	0.21%***	0.99***	0.98	1
New Zealand	0.06%	0.94***	0.92	0

Table 6
Performance measurement for global fundamentally weighted portfolios using Carhart's four-factor model
This table presents the regression results from applying Carhart's four-factor model for explaining the monthly excess returns of the global portfolios from July 1982 to June 2008. All the estimates are obtained by OLS. Newey-West robust standard errors are used. The regression R^2 is adjusted for degrees of freedom. *, **, and *** mean significant at the 10%, 5%, 1% level, respectively. The last column Rej. denotes the result of the multiple testing procedure as obtained by the Romano and Wolf (2005)-StepM method. Under test is respectively the null hypothesis that the considered fundamentally weighted portfolio does not beat the zero benchmark (H_0: a = 0). Rej. equaling 1 indicates the rejection of the null hypothesis, which suggests that the considered fundamentally weighted portfolio actually outperforms the traditional benchmark.

	a	b	s	h	w	R^2	Rej.
Book Value	0.09%*	0.99***	0.05***	0.22***	-0.01	0.98	0
Cash Flow	0.18%***	0.95***	0.04*	0.24***	0.03	0.95	1
Dividends	0.25%***	0.87***	0.01	0.27***	0.02	0.90	1
Employees	0.09%	1.00***	0.09***	0.33***	0.03	0.92	0
Income	0.20%***	0.94***	0.03	0.22***	0.03	0.94	1
Net Payout	0.18%	0.90***	0.05*	0.21***	0.07	0.82	0
Sales	0.16%**	1.01***	0.02**	0.19***	0.00	0.96	0
Composite	0.19%***	0.94***	0.02	0.25***	0.01	0.96	1

Table 7
Performance measurement for country-specific fundamentally weighted portfolios using Carhart's four-factor model
This table presents the regression results from applying Carhart's four-factor model for explaining the monthly excess returns of the country-specific composite portfolios. The International Monetary Fund (IMF) classification denotes whether a country is developed (advanced economies) or emerging (emerging and developing economies). The time period under review for each country ranges from the inception of returns for that country (see Table 1) to June 2008. All the estimates are obtained by OLS. Newey-West robust standard errors are used. The regression R^2 is adjusted for degrees of freedom. *, **, and *** mean significant at the 10%, 5%, 1% level, respectively. The last column Rej. denotes the result of the multiple testing procedure as obtained by the Romano and Wolf (2005)-StepM method. Under test is respectively the null hypothesis that the considered fundamentally weighted portfolio does not beat the zero benchmark (H_0: a = 0). Rej. equaling 1 indicates the rejection of the null hypothesis, which suggests that the considered fundamentally weighted portfolio actually outperforms the traditional benchmark.

Country	IMF Classification	a	b	s	h	w	R^2	Rej.
				Africa				
Egypt	Emerging	0.42%	0.89***	0.04	0.08***	0.03	0.89	0
Morocco	Emerging	-0.19%*	1.05***	0.06***	0.03**	-0.03*	0.98	0
South Africa	Emerging	0.06%	1.00***	0.08***	0.15***	-0.04***	0.98	0
				America				
Argentina	Emerging	0.11%	0.97***	0.03	0.05	-0.04	0.94	0
Brazil	Emerging	0.28%	0.90***	-0.11	-0.03	-0.01	0.83	0
Canada	Developed	0.38%***	0.89***	-0.01	0.10***	0.01	0.92	1
Chile	Emerging	0.10%	1.08***	0.04*	0.02	0.06*	0.95	0
Colombia	Emerging	[NA]						
Mexico	Emerging	0.18%	0.96***	0.07**	0.21***	-0.06*	0.95	0
Peru	Emerging	0.27%	1.03***	0.01	0.09***	-0.07*	0.90	0
USA	Developed	0.26%***	0.94***	-0.07***	0.19***	-0.03	0.95	0
Venezuela	Emerging	[NA]						
				Asia				
China	Emerging	0.56%*	0.99***	0.20***	0.11***	0.12**	0.95	0
Hong Kong	Developed	0.18%*	0.97***	-0.01	0.09***	-0.03	0.97	0
India	Emerging	0.56%***	0.97***	-0.12***	0.08*	0.00	0.88	0
Israel	Developed	0.44%**	0.89***	-0.01	0.11***	-0.06	0.86	0
Japan	Developed	0.18%***	0.98***	-0.08**	0.19***	0.00	0.97	0
Malaysia	Emerging	0.16%**	0.94***	0.00	0.04**	-0.01	0.98	0
Pakistan	Emerging	0.26%	1.04***	0.00	-0.02	-0.09*	0.94	0
Philippines	Emerging	0.07%	0.91***	-0.03	0.05*	-0.08	0.89	0
Singapore	Developed	0.26%**	1.00***	0.02	0.15***	0.00	0.95	0
South Korea	Developed	0.50%**	1.04***	-0.10*	0.04	0.00	0.94	0
Sri Lanka	Emerging	[NA]						

Table 7 (*continued*)

Country	IMF Classification	a	b	s	h	w	R^2	Rej.
Taiwan	Developed	-0.01%	0.87***	-0.08*	0.13***	0.01	0.88	0
Thailand	Emerging	0.44%**	0.96***	0.02	0.24***	0.02	0.88	0
Turkey	Emerging	0.24%	1.00***	-0.03	0.20***	0.08**	0.97	0
				Europe				
Austria	Developed	0.24%***	0.96***	0.03	0.08***	0.02	0.95	1
Belgium	Developed	0.07%	1.02***	0.01	0.05**	0.04	0.96	0
Czech Republic	Developed	[NA]						
Denmark	Developed	0.01%	0.96***	0.10***	0.14***	-0.03	0.89	0
Estonia	Emerging	[NA]						
Finland	Developed	0.29%*	0.79***	-0.03	0.25***	0.00	0.85	0
France	Developed	0.22%***	0.97***	-0.05	0.09***	-0.05	0.94	0
Germany	Developed	0.23%***	0.95***	-0.04**	0.07***	0.02	0.98	1
Greece	Developed	0.42%***	0.97***	-0.04	0.01	-0.06	0.94	0
Hungary	Emerging	0.20%	0.99***	-0.12***	0.09***	0.10**	0.98	0
Ireland	Developed	0.24%	0.90***	0.03	0.10***	0.01	0.86	0
Italy	Developed	0.19%**	1.00***	-0.07**	0.15***	-0.01	0.96	0
Luxembourg	Developed	0.07%	0.91***	0.03	0.00	0.07	0.90	0
Netherlands	Developed	0.08%	1.02***	-0.02	0.13***	-0.02	0.91	0
Norway	Developed	0.12%	0.96***	0.01	0.04*	0.04	0.89	0
Poland	Emerging	0.53%**	0.95***	-0.03	0.01	0.04	0.94	0
Portugal	Developed	0.37%***	0.96***	0.02	0.01	0.03	0.92	1
Russia	Emerging	0.82%	0.97***	-0.16*	0.04	0.48**	0.70	0
Spain	Developed	0.20%***	0.99***	0.01	0.05***	0.04**	0.98	1
Sweden	Developed	0.20%	0.90***	0.01	0.20***	0.03	0.93	0
Switzerland	Developed	0.05%	1.03***	-0.05*	0.11***	0.01	0.95	0
United Kingdom	Developed	0.14%**	1.00***	-0.03**	0.09***	-0.03	0.97	0
				Oceania				
Australia	Developed	0.20%***	1.00***	-0.04**	0.05***	0.01	0.98	1
New Zealand	Developed	-0.14%	0.98***	0.06	0.15***	0.02	0.94	0

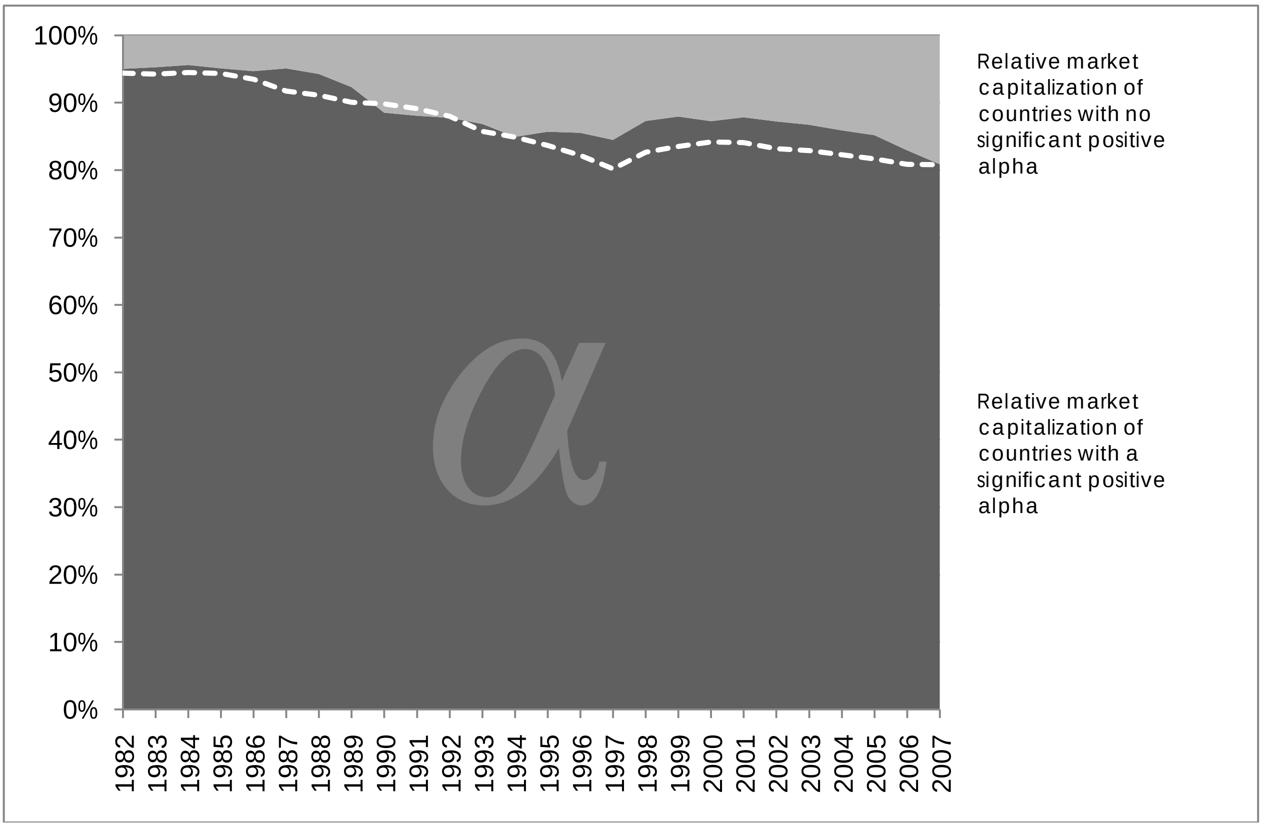

Fig. 1. Economic contribution to the world market portfolio of countries exhibiting a significant positive fundamentally weighted portfolio alpha on a 5% level or better (see Table 7). The dark grey shaded area shows the relative contribution of outperforming country-specific fundamentally weighted portfolios in terms of market value to the world market portfolio, and the light grey shaded area the relative contribution of non-outperforming country-specific fundamentally weighted portfolios at the end of June of each year between 1982 and 2007. The white dashed line separates the two groups according to the worldwide composite fundamental metric instead of the worldwide market value.