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# Emerging equity markets in a globalized world[☆]

Geert Bekaert[a], Campbell R. Harvey[b,*], Tomas Mondino[c]

[a] Columbia University and CEPR
[b] Duke University and NBER
[c] Columbia University

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ABSTRACT

Does the globalization process of the past 25 years obviate the need to segregate global equities into developed and emerging market buckets? We argue the answer is no. Emerging equity markets differ in a statistically significant fashion from developed markets, featuring much lower levels of GDP per capita and equity integration. They also have significantly lower stock market development levels and, on average, feature lower valuation ratios. Emerging markets have morphed into high-beta investments that are highly correlated with developed markets. The historical performance of emerging market investing is much improved by replacing value-weighted indices with alternative weighting schemes, including equal weights, valuation-based weights, and GDP weights.

## 1. Introduction

Thirty years ago, the World Bank organized the conference "Portfolio Flows to Emerging Markets." At the time, the World Bank had recently compiled the first ever database of emerging market equity returns. Foreign portfolio (as opposed to direct) investment was relatively new. The theme of the conference was to improve understanding of the risks that portfolio investors faced in their emerging market investments and to study why emerging markets were different from developed markets.[1] Practitioners at the conference touted emerging market investment as a "free lunch," featuring high returns and very low correlations with developed market returns.

Today, emerging equity markets are a well-established asset class, prompting some to suggest we should not bother to distinguish between emerging and developed markets. Even twenty years ago, Saunders and Walter (2002) claimed that continual capital market liberalization across developing countries obviated the need to separate emerging and developed equity market classes. Their claim raises the general question of what constitutes an emerging market and whether a country's degree of development can be ranked using objective criteria. Benchmark providers, such as MSCI and FTSE Russell, have their own methodologies to differentiate developed from emerging markets with GDP per capita being a main criterion. In addition, they use a mix of quantitative and qualitative criteria

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* Corresponding author.
*E-mail address:* cam.harvey@duke.edu (C.R. Harvey).

[1] See Claessens and Gooptu (1993)

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regarding the size and liquidity of the listed stocks as well as the regulatory environment, and they review the status of the constituent countries every year. Our goal is to use simple quantitative criteria to approximate this complicated process. In addition to GDP-per-capita data, we investigate an indicator of capital market openness (de jure degree of integration), a stock market development indicator (market capitalization to GDP), and valuation ratios, which may be associated with the de facto degree of integration (see Bekaert et al., 2011, BHLS, henceforth).

We show emerging markets feature significantly lower values than developed markets on all four indicators. We standardize these indicators to continuously rank developed, emerging, and frontier markets on their degree of development; frontier markets constitute a category of less-established stock markets, ranking below emerging markets. In particular, we use z-scores relative to the mean and standard deviation of these indicators for the developed markets. We then aggregate the z-scores across indicators and apply a formal clustering algorithm to classify countries into three groups. First, the group means are highly significantly different between groups 1 and 2, suggesting the two groups should be treated as separate asset classes. Second, associating group 1 with developed markets and group 2 with emerging markets, we find that the MSCI cut-off value for emerging versus developed markets generally ranks countries similarly to the clustering algorithm, with a few notable exceptions. Our results suggest, however, that a number of emerging markets have such low development status they are classified in group 3. For 2000 and 2015, these countries include the well-known BRIC countries.

It is conceivable that the behavior of emerging market equity returns has changed such that they may no longer deserve to be a separate asset class.[2] After all, the practitioners at the World Bank conference 30 years ago erroneously extrapolated emerging market return characteristics from past data. The capital-market liberalization process was always bound to change the data-generating process for emerging market returns. In particular, we would anticipate emerging market equities' expected returns to decrease, at least in the short run, and their correlations with developed markets to increase, and that is indeed what happened (Bekaert and Harvey, 1997; Bekaert and Harvey, 2000, and Henry, 2000). We show that over the last 25 years, emerging market equities transformed from an asset class that exhibited very low correlation and low beta with the rest of the world's equity markets to an asset class with a relatively high correlation to these markets.[3] Given that part of the increased correlation reflects increased beta, emerging market equities is now a high-beta asset class, risky but with potentially high expected returns.

We analyze correlation dynamics over time, documenting within-group correlations of developed market versus emerging market portfolios and testing for trends in correlations and their components (betas, factor volatilities, and country-specific volatilities). We provide a variance decomposition of correlation variation over time. This decomposition is important because factor volatility changes tend to be transitory, whereas other components may experience permanent changes associated with development and integration. Changes in beta obviously affect expected returns. We show that beta variation is a dominant contributor to the time series variance of correlations in emerging markets, but not in developed markets. Lastly, although return correlations are typically computed with monthly returns, we show that correlations decrease substantially as the return horizon for emerging market equities is lengthened, but the same is not true in the developed markets. Individual emerging markets also feature more-skewed distributions than developed markets, but the emerging markets index is as negatively skewed as the developed markets index.

The final question we address is the size of the allocation a diversified global equity portfolio should have to emerging market equities. The relative market capitalization of emerging markets is much lower than their relative economic weight, thus a market-capitalization-based benchmark can be viewed as a lower bound on a portfolio's allocation to emerging markets. We show that value-weighted emerging market investments have had a negative alpha over the last 25 years. Alternative value-weighted emerging market indices provide similar results, although there is considerable variation in the composition of the emerging market portfolios among different index providers. We examine whether alternative weighting schemes provide better performance and find that equal-weighted portfolios (whose rebalancing resembles a value strategy), portfolios inversely weighted by market capitalization to GDP, and portfolios inversely weighted by valuation ratios deliver significant positive alphas relative to the standard value-weighted emerging market index returns. These same weighting schemes, however, do not benefit developed market portfolios. Using GDP weights instead of market capitalization weights also delivers better performance in emerging market portfolios. Momentum, reversal, betting-against-beta, and idiosyncratic risk portfolios fail to outperform. To minimize transaction costs for the alternative strategies, we employ annual rebalancing. The negative excess return performance of the major value-weighted indices is not due to the large weight assigned to (the investable shares of) the Chinese stock market. We suggest that using alternative country weights, an allocation to emerging markets larger than market capitalization is likely warranted. The greater diversification benefits over longer horizons may further enhance the attractiveness of emerging markets for long-horizon investors, but we find the long-run correlation benefits are negated by higher long-run volatility.

We organize our paper as follows. The second section provides an empirical definition of an emerging market and ranks countries according to their degree of development. In the third section, we explain the unique risk characteristics of emerging markets as well as their evolution through time. We examine the strategic asset allocation to emerging markets in the fourth section and offer concluding remarks in the final section.

[2] Kritzman (1999) defines an asset class as a set of homogeneous securities, relatively lowly correlated with existing asset classes, with enough investment capacity and which, when added to an existing portfolio, raises utility.

[3] Harvey (1995) repors a median beta of 0.22 around the time of the liberalizations.

## 2. Defining an emerging market

In this section, we describe the various indicators we use to derive an overall development/integration indicator. We then employ a clustering algorithm to organize the countries into various groups. We list the countries in our sample in the appendix.

### 2.1. Emerging market indicators

Emerging market investments may not constitute a separate asset class if effectively integrated into global capital markets. In an integrated world market, projects of the same risk level should command the same expected return, regardless of location. If a market is not integrated, we refer to the market as segmented. A continuum of possibilities between full segmentation and full integration exists. Many emerging markets are not fully integrated into world markets (see Bekaert and Harvey, 1995, and Bekaert et al., 2011). Segmentation is first and foremost caused by regulations that make it difficult for a foreign investor to buy equity in a particular country. Changes in global equity markets and the more-general financial liberalization process that occurred at the end of the 1980s and throughout the 1990s relaxed many regulations, encouraging greater institutional and retail investment in what many considered a new asset class.

We first focus on actual measures of *de jure* integration (regulatory barriers to foreign investment) using data from the International Monetary fund (IMF). The data are based on the work of Fernández et al. (2016), as updated on Uribe's website,[4] using information on capital account openness to score countries on the basis of their capital controls. They differentiate between asset classes (equities, bonds, money markets, and so forth) and between restrictions on purchases and sales of residents and nonresidents. We convert the number-of-restrictions index into a (0,1) degree-of-openness indicator, which ranges from zero (fully segmented) to one (fully integrated). We focus on the equity category and separately examine restrictions on outflows (purchases/sales of foreign securities) and inflows (purchases/sales of domestic securities). Fig. 1 shows the average degree of integration over time for developed markets in orange and for emerging markets in blue (we use the MSCI classifcations). The shaded areas represent 95% bootstrapped confidence intervals. The differentiation between the two types of markets is distinct; developed markets are close to fully integrated, but the degree of integration for emerging markets is less than 50%.

In Table 1, we provide simple panel regressions of these country-specific indicators on a constant, which measures the degree of integration for developed markets, and a dummy for emerging markets. The results confirm the picture that emerges from Fig. 1, but also show that the degree of integration is lower for outflows than for inflows for both groups of countries. We add trend terms to the regressions to differentiate between trends for developed and emerging markets, as shown in the next columns of the table. No coefficients are significant at the 5% level, and the trend coefficients for emerging markets are negative.

Fig. 1 reveals a mild inverse-U pattern, suggesting that de jure globalization has not really improved since 1995. These data do not capture the major liberalizations that happened at the end of the 1980s and in the early 1990s, because our sample period begins in 1995. And because our sample ends in 2017, the data do reflect that many countries reimposed capital controls in the first decade of the 21st century. The cross-country averages hide very different patterns across countries. For example, Korea liberalized further in the late 1990s and became fully open, but imposed stricter reporting requirements in 2011 for nonresident purchases of Korean shares and resident purchases of foreign shares, causing its openness index to drop to 0.75. Argentina liberalized after 1991, but following the collapse of the nation's currency board in 2002 reinstituted capital controls, which lowered its openness index to zero; a more liberal regime in the later years of the sample period allowed the index to recover to 1.0. Chile followed, perhaps, the expected pattern, starting at zero and moving to 0.75 at the end of the sample. Pakistan followed the opposite pattern. The indicators are quite coarse, however. For example, despite efforts to provide limited access to local capital markets, the indicators classified China as fully closed in 2019, as was Brazil. Thus, full de jure segmentation does not preclude some degree of investability for developed market investors. Consequently, measures of effective openness are important.

Most benchmark index providers use GDP per capita as their main criterion to determine whether countries belong in the developed or emerging market group. In Table 2, we show the same panel regression as in Table 1, but for annual natural logs of GDP per capita (measured in dollars). Not surprisingly, we observe a significant and economically substantial difference between emerging and developed markets. The constant and emerging market dummy correspond to an average per capita GPD level of around $36,000 for developed markets and less than $5000 for emerging markets. The trend coefficient for emerging markets is roughly twice as high as for developed markets. This significantly positive trend indicates convergence in development levels, but the convergence rate is very slow, implying convergence only after 60 years.

Index providers often use other criteria as well. They must ensure the stock markets included in their indices are viable and sufficiently liquid to absorb large capital flows. Hence, a stock market development indicator, such as market capitalization to GDP, is important. Table 2 shows that the average market-cap-to-GDP ratio is slightly less than one for developed markets and about 40% for emerging markets with the difference highly statistically significant. The trend upward in market development is statistically significant, but does not differ for emerging and developed markets. That is, we do not expect convergence of market development levels, which indicates that development levels are relatively fixed over time.[5]

Emerging markets represent a smaller part of world market capitalization than of world GDP. In the late 1980s, the United States and Japan accounted for 46.3% of world GDP, whereas China accounted for less than 1.5%. By 2019, China's share had grown to

[4] http://www.columbia.edu/ mu2166/fkrsu/

[5] The lack of convergence is also apparent within the two groups of countries.

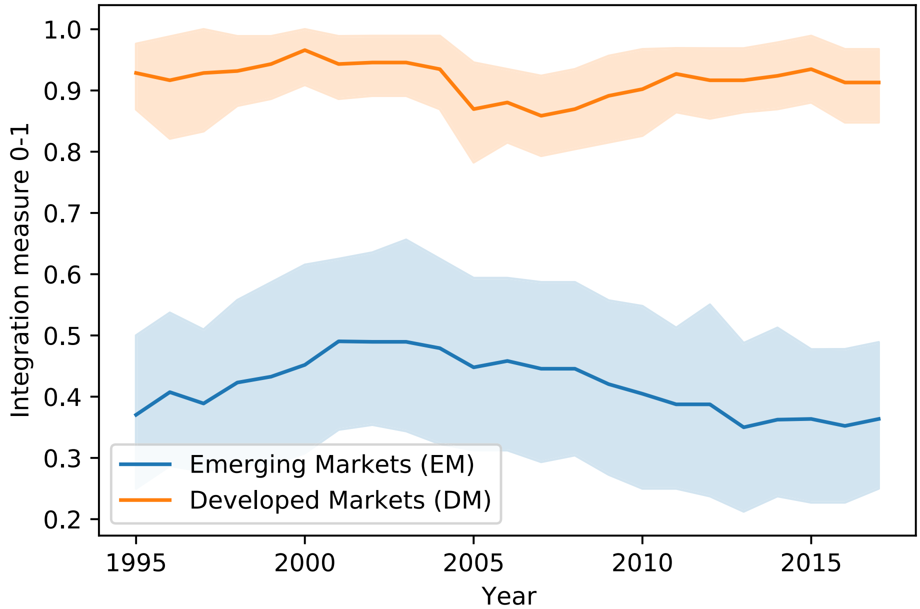



**Fig. 1.** Degree of equity integration based on regulatory environment.
Time-varying DM and EM equity integration. Equity integration is calculated as 1 minus the *de-jure* average restriction index from Fernández et al. (2016). We classify countries into EM and DM using the MSCI classification. The solid line and shaded areas indicate the median and the bootstrapped 95% confidence intervals, respectively.

**Table 1**
De Jure integration.

| | *Equity Integration Measure Ranges from 0–1* | | | | | |
|---|---|---|---|---|---|---|
| | Average | Inflow | Outflow | Average | Inflow | Outflow |
| Constant | 0.917*** | 0.945*** | 0.889*** | 0.917*** | 0.945*** | 0.890*** |
| | (0.012) | (0.014) | (0.014) | (0.012) | (0.014) | (0.014) |
| EM | −0.497*** | −0.422*** | −0.572*** | −0.499*** | −0.422*** | −0.576*** |
| | (0.017) | (0.019) | (0.020) | (0.017) | (0.019) | (0.020) |
| Trend | | | | −0.001 | 0.002 | −0.004* |
| | | | | (0.002) | (0.002) | (0.002) |
| *EM* × *Trend* | | | | −0.002 | −0.002 | −0.001 |
| | | | | (0.003) | (0.003) | (0.003) |
| $R^2$ | 0.453 | 0.315 | 0.440 | 0.454 | 0.316 | 0.445 |
| Observations | 1062 | 1062 | 1062 | 1062 | 1062 | 1062 |

This table shows regressions of equity integration measures described in Section 2 on an emerging market dummy (MSCI classification) and trend dummies. The equity integration measures are 1 minus the average, inflow and outflow restriction measures from Fernández et al. (2016). The regression includes 29 emerging markets (540 country-year observations) and 24 developed markets (522 country-year observations) based on the time-varying MSCI classification. Data sample is from 1995 to 2017. ***,**, and * indicate significance at 5%, 1%, and 0.1%, respectively.

16.3%, while the combined share of the United States and Japan fell to 29.6%. China's share in 2019 would be even larger if we had PPP-adjusted the GDP numbers.

Economic reasons, in part, explain the gap between the share of world GDP and the share of world equity. In many developing countries, banks provide the main source of a firm's financing. Across developed countries, strong variation in financing patterns occurs (see, e.g., Beck et al., 2008) and the relative size of equity markets varies wildly. For example, Germany and Italy have relatively small equity markets, whereas the United States and United Kingdom have relatively large stock markets. Even with equity financing being a viable financing channel in many large emerging markets, the apparent lack of future convergence is interesting to note. A final set of indicators are valuation measures, which can inform the de facto (effective) degree of integration (see Bekaert et al., 2011). Relaxing restrictions on foreign investors does not necessarily lead to integration because other factors may effectively segment the market from global capital markets. A good example is extreme political risk, which may exclude important institutional investors with a mandate to invest in investment-grade countries. Another example is poor corporate governance. These factors may serve to segment markets, but can also create expected return opportunities for global investors. For example, Erb et al. (1996) argued that the market prices political risk. Therefore, emerging markets with severe political risk may offer attractive expected returns if the political risk

**Table 2**
Emerging market characteristics.

| | Log GDP per capita | Market cap./GDP | Price/Earnings ratio | Dividend yield |
|---|---|---|---|---|
| Constant | 10.496*** | 0.948*** | 17.634*** | 2.772*** |
| | (0.031) | (0.034) | (0.292) | (0.067) |
| EM | −2.044*** | −0.559*** | −2.992*** | 0.252*** |
| | (0.043) | (0.047) | (0.407) | (0.093) |
| Trend | 0.037*** | 0.016*** | −0.196*** | 0.048*** |
| | (0.005) | (0.005) | (0.044) | (0.010) |
| EM × Trend | 0.034*** | −0.002 | 0.270*** | −0.021 |
| | (0.006) | (0.007) | (0.062) | (0.014) |
| $R^2$ | 0.722 | 0.139 | 0.068 | 0.034 |

This table shows regressions of various statistics on an emerging market (MSCI classification) dummy and trend dummies. Characteristics are the natural logarithm of GDP per capita in constant dollars, the equity market value to GDP ratio, the price to earnings ratio (pe), and the dividend yield (dy). Sample is from 1995 to 2020. PE ratios are "derived by dividing market value by the total earnings, thus providing an earnings-weighted average of the PEs of the constituents… Negative earnings per share are treated as zero" (Datastream Global Equity Indices User Guide). [***], [**], and [*] indicate significance at 5%, 1%, and 0.1%, respectively.

factor eventually reverts to normal levels. More generally, specific risk factors that cause partial segmentation of emerging markets from global markets may cause emerging markets to trade more cheaply than developed markets. The result is an emerging market discount, which has been apparent since the mid-1990s.

The price-to-earnings (PE) ratio may reflect to a considerable extent a country's unique industry structure. Bekaert et al. (2011) developed a measure of the degree of effective market segmentation (SEG) using valuation metrics, carefully controlling for cross-country variation in industry composition. The SEG measure views each country as a basket of industries, weighted by market capitalization. The measure takes absolute differentials between the industry earnings yield (inverse of the PE ratio) and the earnings yield of the respective industry at the world level for 38 different industries. The market-capitalization-weighted sum of the absolute differentials is the country segmentation measure.

If countries are integrated, the SEG measure should be very small and relatively constant through time, because the discount rate and the growth rate of (expected) dividends should converge for the same industries in different countries if these countries are truly integrated. This concept of market integration assumes that industries have identical systematic risk across the globe and that growth opportunities are industry specific, but global in nature. The latter assumption is plausible if growth opportunities are driven primarily by technological factors and if capital markets are totally open. BHLS showed a downward trend in segmentation, with earnings yield differentials converging worldwide. The earnings yield differential for emerging markets was still significantly above that of developed markets, however, by the end of their sample. They concluded that emerging markets were still not fully integrated within global capital markets and were rightfully a separate asset class. Eun and Lee (2010), studying risk–return distance between developed and emerging markets, also provided evidence consistent with convergence, but concluded that emerging markets were still distinct, as did Carrieri et al. (2013) based on a study of implicit investment barriers in emerging markets.

Inspired by BHLS, Table 2 shows the panel regressions for two valuation ratios: the PE ratio (as defined by DataStream) and the dividend yield.[6] The emerging-market valuation discount is visible and statistically significant: emerging markets have a PE ratio about three points lower than developed markets and a dividend yield about 25 basis points (bps) higher. Both measures show substantial cross-country dispersion. The significant trend coefficients indicate convergence of these ratios across the two country groups within 10 years.[7]

### 2.2. Aggregating the indicators

We now have several indicators that differentiate emerging from developed markets in a statistically significant manner. In order to create an aggregate score of these indicators, we must make them unitless. We first compute z-scores for the developed markets, that is, for each statistic for developed country $i$ at time $t$, we subtract the panel mean and divide by the panel standard deviation. In this way, we create a series of numbers centered around the developed market mean with a unit standard deviation. The developed market classification uses the MSCI definitions. For emerging and frontier markets, we also compute analogous z-scores, but use the means and

[6] We lack the data to control for industry structure, but a focus on countrywide PE ratios facilitates the analysis of different country weighting schemes, which we explore in Section 4.

[7] As an aside, the emerging market discount was not visible for the domestic Chinese A-share market until after 2009. Using portfolios differentiated across various value-relevant characteristics, including industry, Bekaert et al. (2021) argue that changing differential growth prospects and a change in ownership away from retail investors to foreign investors helped reverse the valuation differential in the Chinese market. Note that the representation of A-shares in the international emerging market indices is still quite limited. Instead, such indices primarily contain cross-listed shares (e.g., in Hong Kong) and so-called homeless shares (Chinese companies that are only listed abroad).

standard deviations computed from the developed market group. We interpret such a number for a particular emerging market statistic as the number of standard deviations the statistic deviates from the developed market mean.

Table 3 shows the properties of the cross-sectional distribution for the resulting statistics for emerging markets. The GDP-per-capita distribution is the furthest away from the developed market one, with the mean 6.4 standard deviations below the developed market mean, and the 75th percentile value still 4.5 standard deviations below the developed market mean. The mean of the equity integration measure is 3.3 standard deviations below the developed market mean, and the 75th percentile value is 1.2 standard deviations below. We observe more overlap between the two group distributions for the valuation ratios, but asymmetry remains. The emerging market means are about 0.5 standard deviations below (PE ratio) and above (dividend yield) the developed market means. The market-cap-to-GDP distribution is slightly more asymmetric, with the 75th percentile value 0.56 standard deviations below the developed market mean. By contrast, we also show the distribution for beta, that is, the each market's beta relative to the MSCI World Index return, which was computed in a rolling, centered fashion with five years of monthly data. Although initially emerging markets had very low betas relative to the world market, the full sample distribution of betas now overlaps substantially with the developed market distribution and offers no meaningful differentiation. The median beta z-statistic is 0.24, consistent with emerging markets currently having relatively high betas.

With these unitless statistics in hand, we can create an aggregate score. We use GDP per capita, equity integration, market cap to GDP, and the PE ratio, which represents valuation. We assign a 0.4 weight to GDP per capita, 0.3 to de jure integration, and 0.15 each to market cap to GDP and the PE ratio. Results using the dividend yield as the valuation measure are very similar. Computing these scores for each country at each point in time results in a large panel of ranked statistics. Table A1 in the appendix shows the ranked list of countries with scores for 2000 and 2015.[8] The rank correlation with the equally weighted approach is 0.995 (0.992) for 2000 (2015). Fig. 2 shows the data for 2000, 2005, and 2015. Each dot represents a country with its rank on the horizontal axis and its score on the vertical axis. Note that the number of countries rose to 55 in 2015 from 49 in 2000. The numbers in 2000 show more dispersion, with a low score of 7.85 for India.

We now use these empirical scores to group countries into top (developed), middle (emerging), and bottom (frontier) groups and to compare the empirical grouping with the grouping MSCI uses. Several techniques are available to implement optimal grouping, but k-means clustering is particularly attractive in this context. This method determines the cut-off points that minimize the squared within-group deviations from the mean. Fig. 3 shows the results for two years, 2000 and 2015; the scores for 2000 are on the horizontal axis and the scores for 2015 are on the vertical axis. The colors indicate the MSCI classification. Blue indicates developed markets for both years, orange indicates emerging markets, and red indicates frontier markets (at least in 2015). Israel and Portugal are in green because they moved from the emerging group to the developed group between 2000 and 2015.

The graph also shows our three-mean clustering results. The vertical dashed line on the right shows the empirical cut-off between the middle and top groups, which we propose as an empirically determined cut-off between emerging markets and developed markets for 2000. Because Greece, Israel, and Korea are to the right of the line, they should have been classified as developed markets rather than as emerging markets; the Czech Republic is on the cusp of being a developed market. The top horizontal dashed line is the cut-off in 2015 between the top and middle groups under optimal clustering. Only one classification is inconsistent with the empirical clusters. Portugal is below the line and thus should be an emerging market, but MSCI classifies it as a developed market. Hungary, Korea, and the Czech Republic are very close to, but not above, the cut-off line. Thus, their classifications as emerging markets are consistent with our empirical clusters.

In 2000, Slovenia, a frontier market, is in the middle rather than the bottom group. Ten emerging markets are in the bottom group: Brazil, China, India, Indonesia, Morocco, Pakistan, Philippines, Russia, Sri Lanka, and Thailand. Interestingly, many of the same countries remain in the bottom group in 2015: Brazil, China, Colombia, Egypt, India, Indonesia, Philippines, Russia, South Africa, and Thailand. Morocco, Sri Lanka, and Pakistan are also in the bottom group; MSCI effectively demoted these countries to frontier status between 2000 and 2015. The set of MSCI emerging markets classified as frontier markets includes the BRIC countries in both 2000 and 2015. It is quite understandable that an index provider would not exclude such big markets (all four of these markets are in the top half in terms of worldwide market capitalization) from its major indices. In contrast, in 2015, the markets that ought to be promoted from a frontier to a developed classification all represent relatively small markets: Argentina, Bahrain, Bulgaria, Kuwait, and Oman (not all of these countries are on the graph, because data for 2000 are not available).

To obtain a more complete picture, and to ensure the results for 2000 and 2015 are representative, Fig. 4 shows properties of the clusters over time relative to the MSCI classifications. In the top panel, the bottom solid line shows the number of countries in the top clustering group (plus one) that are candidates for developed markets; the top solid line shows the total number of countries (plus one) in the top plus middle groups that are candidates for both developed and emerging markets. The dashed lines show the corresponding number of countries for the MSCI classifications. The number of developed countries is very stable in the MSCI classifications. The clustering methodology classifies more countries as developed, except toward the end of the sample where the numbers converge. Fewer countries are in the middle emerging group compared to the MSCI classification over most of the sample. Between 2010 and 2015, however, the sum of developed and emerging countries under clustering exceeds the number of MSCI emerging and developed countries. As previously discussed, multiple frontier (emerging) markets are classified in the middle (bottom) group under clustering. In the bottom panel, we show the average z-scores in the top and middle groups under clustering and under the MSCI classification (the shading represents the 90% confidence interval). The top line is by definition at zero for the MSCI classification, but clearly the

[8] We also computed scores with an equal-weighted method delivering almost identical results.

**Table 3**
The distribution of standardized emerging market characteristics.

| Characteristic | Mean | Std. dev. | Min | 25% | 50% | 75% | Max |
|---|---|---|---|---|---|---|---|
| eq integration | −3.275 | 2.066 | −6.469 | −4.932 | −3.416 | −1.172 | 0.538 |
| log gdppc | −6.356 | 3.622 | −13.531 | −9.158 | −5.755 | −4.548 | 0.915 |
| mv/gdp | −0.669 | 0.346 | −1.251 | −0.814 | −0.737 | −0.564 | 0.277 |
| pe | −0.580 | 0.700 | −2.055 | −0.979 | −0.618 | −0.078 | 0.603 |
| dy | 0.512 | 1.221 | −1.255 | −0.267 | 0.288 | 0.829 | 3.916 |
| beta | −0.100 | 1.480 | −3.585 | −0.852 | 0.238 | 0.873 | 2.425 |

Summary statistics of distance between Emerging Market characteristics and Developed Markets as measured by a *z*-score using the DM mean and DM standard deviation for each country characteristic; equity integration (see Table 1), GDP per capita in logs (log gdppc), market capitalization over GDP (mv/gdp), the price earnings ratio (pe), the dividend yield ratio (dy), and the market beta. All valuation ratios are from Datastream equity indices. The market beta uses market excess returns (in USD) relative to the DM index excess returns calculated using five-year centered rolling windows. The sample is from 1995 to 2017.

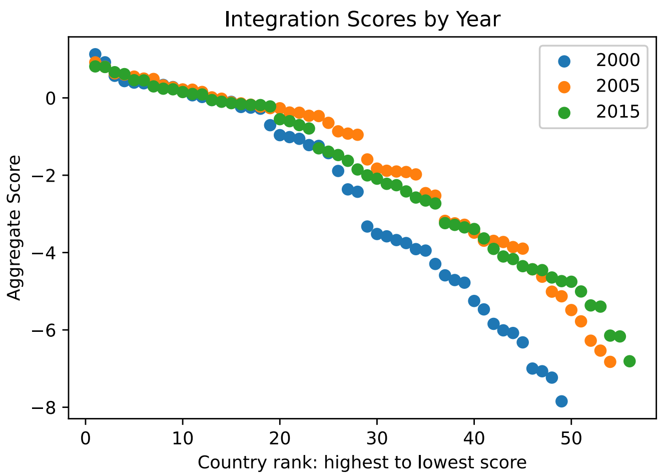



**Fig. 2.** Emerging market indicator scores.
This figure shows the aggregate (weighted) score by country rank in three years: 2000, 2005, and 2015. The aggregate score (weighted average z-score) is calculated using the variables (1) log GDP per capita, (2) equity integration, (3) MV-to-GDP, and (4) price-to-earnings ratio and the weights are 0.4, 0.3, 0.15 and 0.15, respectively, as explained in Section 2. A score of −2 means the country is 2 standard deviations below the mean for developed countries.

clustering methodology delivers average z-scores indistinguishable from the MSCI classification for its top group. For the emerging market cut-off, the MSCI line is 0.5 to 1.0 standard deviations below the line for the emerging markets according to the clustering technique.

We can test whether the z-scores are statistically different across classifications using simple differences in means tests. The first three columns of Table 4 show the average z-scores each year for the three clustering groups. Columns (4) and (5) show the average z-scores for the MSCI emerging and frontier markets, respectively. The last four columns present various tests between average z-scores. Under the clustering technique, the z-scores are both economically and statistically different cross the three groups.

Economically, the differences between developed and emerging markets and between emerging and frontier markets represent between two and three standard deviations, with the differences decreasing slightly over time. Not surprisingly, these differences are highly significant, generating zero *p*-values for all years, as shown in columns (6) and (7). The average z-score for the MSCI emerging markets, as previously mentioned, is about one standard deviation below the clustering emerging market z-score. Not surprisingly, the z-scores for the MSCI frontier markets are much higher than the z-scores based on the clustering groups. In fact, except for the last four years in the sample, they are above the average z-scores of the emerging markets. That is, MSCI frontier markets are closer to developed markets than emerging markets are in terms of the indicators we study. In fact, for half of the years, the average z-score of emerging markets is significantly lower than the average z-score of frontier markets (see column (9) in Table 4). In column (8), we test the difference in average z-scores between the emerging markets classified according to the clustering method and to the MSCI classification. The differences are significant at the 10% level for all years and significant at the 5% level in all but four years.

To conclude, our empirical ranking coincides closely with the MSCI classification for the split between emerging and developed, but the emerging and frontier market cut-off suggested by empirical clustering is very different from the cut-off MSCI uses. We find that many well-known emerging markets would be classified as frontier markets if based on objective criteria. Until very recently, the set of MSCI frontier markets is actually closer to developed markets than are emerging markets, based on our four indicators of development and integration. This finding is likely attributable to the fact that MSCI primarily relies on a development indicator to distinguish

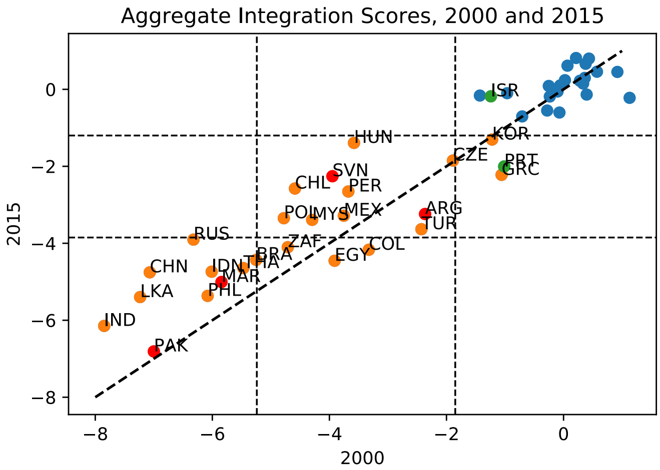



**Fig. 3.** Emerging market indicator scores.
This figure shows each country's scores in 2000 and 2015. Orange circles are EM countries, blue circles are DM countries, green circles are EM countries that changed from EM to DM during this time, and red circles are frontier markets FM in 2015. The aggregate score (weighted average z-score) is calculated using the variables (1) log GDP per capita, (2) equity integration, (3) MV-to-GDP, and (4) price-to-earnings ratio and the weights are 0.4, 0.3, 0.15 and 0.15, respectively.

between emerging and developed markets, and uses primarily size and liquidity requirements and market accessibility criteria to distinguish between emerging and frontier markets (=MSCI). In contrast, we provide a dynamic, transparent classification method based on measurable and objective criteria. Our classification method may be useful for investors. Frontier markets that are much more "developed" than many emerging markets according to our indicator may be prime candidates for future migrations to emerging market status. More generally, there may be valuation implications to being "under-" or "over-"classified. An international investment process may also benefit from a more continuous ranking of countries rather than the coarse categories employed by the benchmark providers. FTSE Russell has in fact recently introduced "advanced" and "secondary" emerging market categories.

## 3. Risk and return characteristics of emerging markets

The combination of home bias and the prevalence of market capitalization benchmarks leads to emerging markets accounting for much less than their economic weight in developed-world investment portfolios. To assess the attractiveness of emerging market equity investments, we now consider the risk and expected return characteristics of emerging market returns.

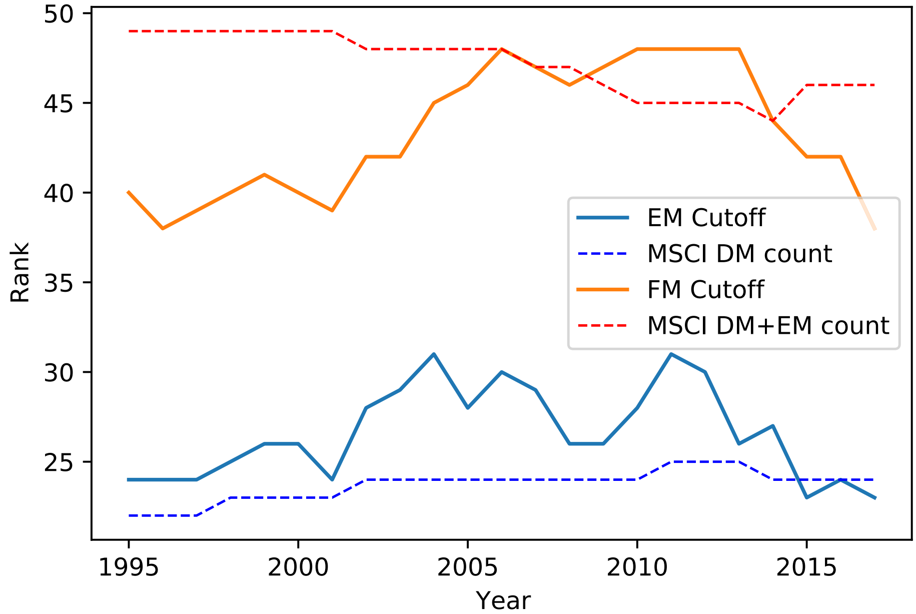
### *3.1. Summary statistics*

All our computations use MSCI indices and are expressed in dollars. Table 5 shows some summary statistics on the first four moments of returns. Panels A and B show unconditional statistics for value-weighted and equal-weighted MSCI indices for developing and emerging markets; the equal-weighted portfolios reflect $1/N$ weights each month. We estimate these moments (mean, standard deviation, skewness, and kurtosis (not excess kurtosis) jointly using a Generalized Method of Moments (GMM) system (Hansen, 1982), described in Appendix A. The system has eight equations and eight unknowns. We use three Newey and West (1987) lags to compute the spectral density at frequency zero of the orthogonality conditions. In Panel C, we compute the moments for a cross-section of countries. To obtain realistic standard errors for our statistics, we set up a large system of all the individual countries for the first four moments. We then compute the average statistics and obtain a standard error using the delta method (see Appendix A).

Individual country statistics are presented in Panel C. The volatility of a typical emerging market is about 11 percentage points higher than the volatility of a developed market (33% versus 22%). Developed markets tend to be negatively skewed, as the results in Panel C show. Emerging markets, however, have higher skewness than developed markets and the difference is statistically significant. The skewness is on average about zero because of recent decreases in skewness, largely due to the global financial crisis. The fact that emerging markets are often positively skewed is not particularly surprising, given that individual stock return distributions exhibit positive skewness—equity is a call option on the firm's assets.

Equity market crashes tend to be systematic, inducing negative skewness at the market level in developed markets. Similarly, an emerging equity market represents a call option on the country's economic development, and country factors remain a dominant source of variation in firm returns (see Phylaktis and Xia, 2006, for an early paper). At the emerging market index level, however, many crashes are global in nature, and thus the skewness of the emerging market index is negative and indistinguishable from the developed market index (See Panel A). We do not find any statistically significant differences in excess kurtosis between developed and emerging markets at the individual or index level.

Panel A shows that over our sample period, the emerging market index registered slightly lower returns than the developed market



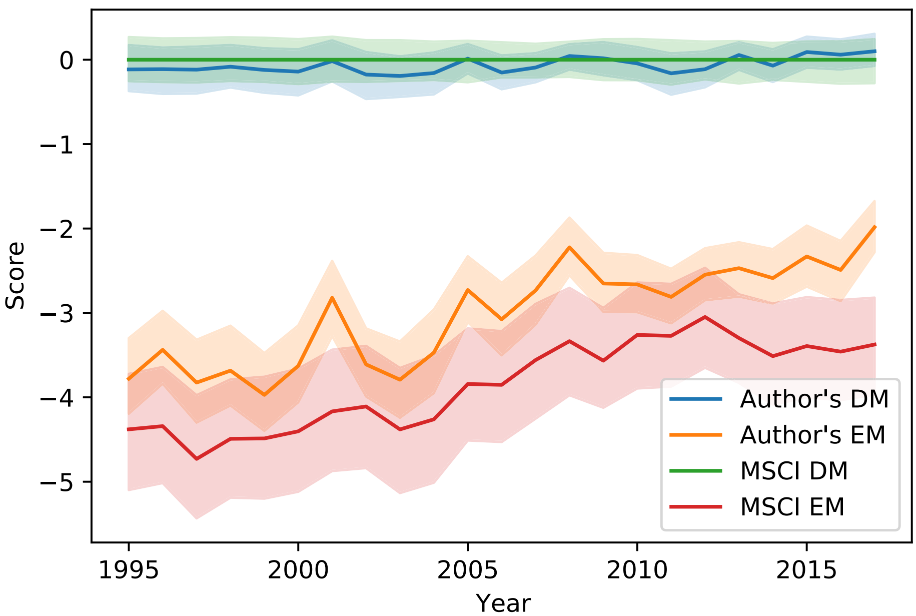




**Fig. 4.** Cluster versus MSCI classification.
These figures compare our cluster-based classification with MSCI. Countries with a rank between the middle group cutoff and 1 are categorized as DM, countries between the middle group cutoff and the bottom group cutoff are EM, and countries ranked beyond the second cutoff are categorized as frontier (FM). The three clusters (DM, EM, FM) are calculated each year by choosing cutoffs that minimize the total squared deviations from the means of weighted scores within a cluster. Black dashed lines show the number of MSCI DM classified countries plus one (lower line), and the number of MSCI DM + EM classified countries plus one (top line). The full lines record these statistics for the cluster-based cutoffs. In the bottom panel, we show the average z-scores corresponding to the DM/EM and EM/FM cut-offs, respectively, for both MSCI and the cluster methodology. Shading around the average lines represents 95% confidence intervals calculated using standard errors of the cross-section.

index. Comparing the results to the average returns recorded by the equal-weighted index in Panel B, the equal-weighted portfolio outperforms the value-weighted one. The difference is economically large, but is not adjusted for rebalancing transaction costs and is not statistically different from zero.

Finally, the emerging market index has a volatility of 23% (Panel A), which is similar to the volatility of an average developed

**Table 4**
Indicator score tests.

| | Cluster | | MSCI | | | Tests | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $\widehat{\mu}_{DM}$ | $\widehat{\mu}_{EM}$ | $\widehat{\mu}_{FM}$ | $\widehat{\mu}_{EM}$ | $\widehat{\mu}_{FM}$ | *p*-val | *p*-val | *p*-val | *p*-val |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| | | | | | | (2)–(1) | (3)–(2) | (2)–(4) | (5)–(4) |
| 1995 | −0.115 | −3.780 | −6.624 | −4.379 | – | 0.000 | 0.000 | 0.029 | – |
| 1996 | −0.112 | −3.437 | −6.218 | −4.341 | – | 0.000 | 0.000 | 0.003 | – |
| 1997 | −0.118 | −3.825 | −6.987 | −4.730 | – | 0.000 | 0.000 | 0.002 | – |
| 1998 | −0.083 | −3.684 | −6.615 | −4.492 | – | 0.000 | 0.000 | 0.006 | – |
| 1999 | −0.121 | −3.971 | −6.759 | −4.487 | – | 0.000 | 0.000 | 0.056 | – |
| 2000 | −0.141 | −3.627 | −6.413 | −4.403 | −3.949 | 0.000 | 0.000 | 0.010 | 0.120 |
| 2001 | −0.016 | −2.821 | −5.950 | −4.167 | −2.875 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2002 | −0.176 | −3.610 | −6.057 | −4.109 | −2.572 | 0.000 | 0.000 | 0.069 | 0.000 |
| 2003 | −0.193 | −3.791 | −6.229 | −4.380 | −1.873 | 0.000 | 0.000 | 0.044 | 0.000 |
| 2004 | −0.158 | −3.470 | −6.163 | −4.261 | −1.088 | 0.000 | 0.000 | 0.009 | 0.000 |
| 2005 | 0.013 | −2.728 | −5.567 | −3.842 | −0.952 | 0.000 | 0.000 | 0.000 | 0.000 |
| 2006 | −0.152 | −3.076 | −5.918 | −3.852 | −1.250 | 0.000 | 0.000 | 0.006 | 0.000 |
| 2007 | −0.092 | −2.733 | −5.634 | −3.558 | −1.877 | 0.000 | 0.000 | 0.004 | 0.000 |
| 2008 | 0.044 | −2.223 | −5.336 | −3.335 | −2.225 | 0.000 | 0.000 | 0.000 | 0.002 |
| 2009 | 0.017 | −2.651 | −5.423 | −3.566 | −2.797 | 0.000 | 0.000 | 0.001 | 0.022 |
| 2010 | −0.044 | −2.662 | −5.314 | −3.261 | −3.020 | 0.000 | 0.000 | 0.028 | 0.253 |
| 2011 | −0.161 | −2.810 | −5.135 | −3.272 | −2.947 | 0.000 | 0.000 | 0.081 | 0.187 |
| 2012 | −0.112 | −2.547 | −4.864 | −3.048 | −2.842 | 0.000 | 0.000 | 0.062 | 0.286 |
| 2013 | 0.056 | −2.470 | −4.958 | −3.298 | −2.866 | 0.000 | 0.000 | 0.004 | 0.118 |
| 2014 | −0.070 | −2.588 | −4.987 | −3.512 | −3.300 | 0.000 | 0.000 | 0.003 | 0.275 |
| 2015 | 0.091 | −2.331 | −4.963 | −3.393 | −3.827 | 0.000 | 0.000 | 0.000 | 0.120 |
| 2016 | 0.060 | −2.491 | −5.061 | −3.459 | −3.935 | 0.000 | 0.000 | 0.001 | 0.098 |
| 2017 | 0.100 | −1.984 | −4.695 | −3.375 | −3.784 | 0.000 | 0.000 | 0.000 | 0.142 |
| Avg N | 25.609 | 16.783 | 10.304 | 23.478 | 10.000 | – | – | – | – |

This table shows the average indicator z-scores by classification and year. In the first three columns countries are classified by the cluster algorithm, while in the fourth to fifth columns they are classified as in MSCI (scores for MSCI DM would be 0 by definition). The last four columns show the *p*-value of difference in means tests for each year. The first (second) tests whether EM is different to DM (FM) in the cluster method, and the third tests whether EM in the cluster is different to EM in MSCI. The fourth and last column tests whether EM and FM scores are significantly different under the MSCI classification. We use $\sqrt{1/N_1 + 1/N_2}$ to calculate standard errors for the test statistics.

market (Panel C). Institutional investors often overestimate the riskiness of emerging equity markets, not realizing how much country-specific volatility is diversified away in the index portfolio. Individual emerging markets have very high volatility ranging, for example, from 27% for South Africa to 48% for Russia over the sample period. The volatility of the emerging market index is therefore low relative to the individual volatilities of separate countries. This indirectly suggests that correlations among emerging markets must be relatively low. Panel C shows an average cross-correlation statistic across emerging markets and across developed markets, for which the weights are volatility weights rather than equal or market-value weights (see Appendix A). This correlation is 0.66 for developed markets, but only 0.45 for emerging markets, with the difference from zero statistically significant.

Fig. 5 examines how the within-group correlation difference varies over time. The figure shows the ratio of the volatility of an equal-weighted portfolio of either developed (blue) or emerging (orange) markets divided by the average volatility of the constituent countries. This ratio converges to one when correlations go to one. We focus on the 20 largest markets so the number of countries is stable over time.[9] Not surprisingly, this statistic confirms that the within-group correlations are higher for developed markets than they are for emerging markets. The within-group correlations have increased substantially over time for both groups, but were unusually high around the global financial crisis and show a more-modest spike for the last few months of the sample, which includes data from the Covid crisis in 2020. (Fig. 5 ends in 2018, but uses data through December 2020, given the centered five-year samples we use.)

### 3.2. Correlation dynamics

From an investment perspective, the absolute risk of emerging markets is largely irrelevant. Typically, investors in developed markets invest only a portion of their portfolio in emerging markets, and thus the correlation between developed markets and emerging markets is an important driver of the ultimate risk borne. When emerging markets were first touted in the early 1990s as appealing investments for global investors, their diversification benefits were emphasized. The emerging market index had a

[9] While this introduces a minor selection issue, the ratio is sensitive to the number of countries, so the number of countries must be kept constant over time and across DM and EM.

**Table 5**
Summary statistics.

| | DM | | EM | | Diff | |
|---|---|---|---|---|---|---|
| | Stat | SE | Stat | SE | Stat | SE |
| *Panel A. index-Level* | | | | | | |
| Mean | 6.885 | (2.97) | 6.628 | (4.38) | −0.257 | (2.62) |
| Std. dev. | 15.184 | (0.82) | 22.367 | (1.28) | 7.182 | (0.83) |
| Skew | −0.670 | (0.22) | −0.706 | (0.27) | −0.036 | (0.21) |
| Kurt | 4.627 | (0.77) | 5.094 | (1.00) | 0.467 | (0.82) |
| *Panel B. Equal-Weighted* | | | | | | |
| Mean | 6.962 | (3.51) | 9.157 | (4.28) | 2.196 | (2.29) |
| Std. dev. | 17.920 | (1.08) | 21.854 | (1.32) | 3.934 | (0.74) |
| Skew | −0.716 | (0.30) | −0.718 | (0.28) | −0.002 | (0.19) |
| Kurt | 5.538 | (1.11) | 5.586 | (1.00) | 0.049 | (0.74) |
| *Panel C. Country-Level Average* | | | | | | |
| Mean | 7.195 | (3.50) | 8.819 | (4.34) | 1.624 | (2.36) |
| St. Dev. | 21.738 | (0.92) | 33.190 | (1.10) | 11.452 | (0.72) |
| Skew | −0.413 | (0.18) | 0.033 | (0.15) | 0.446 | (0.14) |
| Kurt | 4.960 | (0.52) | 5.621 | (0.31) | 0.661 | (0.49) |
| Average Corr | 0.659 | (0.03) | 0.454 | (0.03) | −0.204 | (0.02) |

This table shows unconditional annualized statistics on monthly excess return data from Jan-1995 to Dec-2020 for DM and EM aggregate and country-level indices. All returns are in dollars. Panel A shows statistics for MSCI indices (DM and EM), while Panel B shows statistics for equal-weighted indices constructed using the annual MSCI classification. The return statistics shown are average returns, standard deviation, skewness and kurtosis (not excess kurtosis). Panel C shows the cross-sectional average and standard error of country-level statistics, including a weighted-average estimate of pair-wise correlations. The sample in Panel C is limited to 21 DM and 20 EM countries with returns available from 1995 to 2020. Average return and standard deviation statistics are in percentage points and annualized. Standard errors (shown in parentheses) are calculated with the Delta method in GMM and use three Newey-West lags.

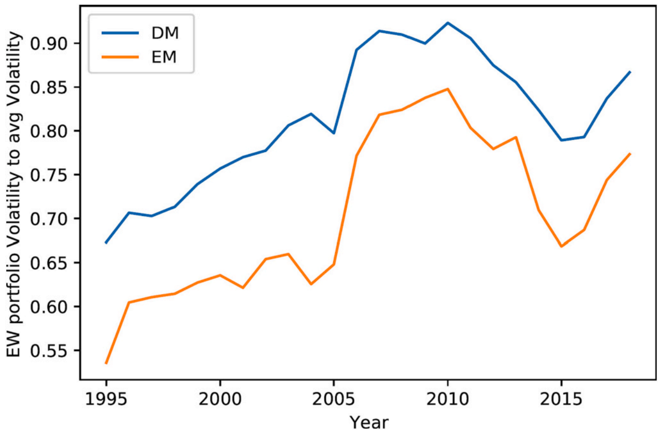
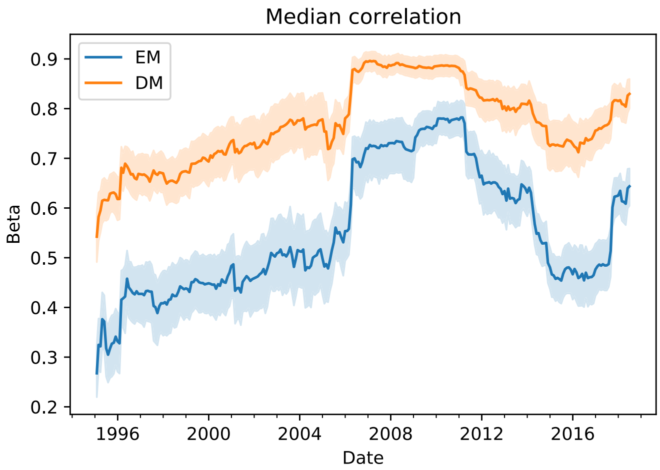



**Fig. 5.** Volatility ratio.
This figure shows the within MSCI class correlation as the ratio of the volatility of an equal-weighted portfolio (of the largest 20 countries selected based on the preceding year's market value) relative to the average volatility of either DM or EM. The volatility series are calculated using five-year (centered) rolling windows.

correlation with the world index of about 0.40, leading to considerable diversification benefits. However, this correlation has increased over time.

The top panel of Fig. 6 shows the correlation of developed, emerging, and frontier markets with the MSCI World Index.[10] For each data point, we use 60 months of data centered around the data point to compute the return correlation. The plot shows the median and 95% confidence intervals for each group, with the 95% confidence intervals for each time period computed using bootstrapping ($n = 10,000$). Obviously, emerging markets are less correlated than developed markets are with the world market, but the steep positive

[10] Note that only the US constistutes a significant fraction of the MSCI World Index. At the end of July 2022, it represents 69.5% of the index; the second largest component of is Japan representing 6% of the index.



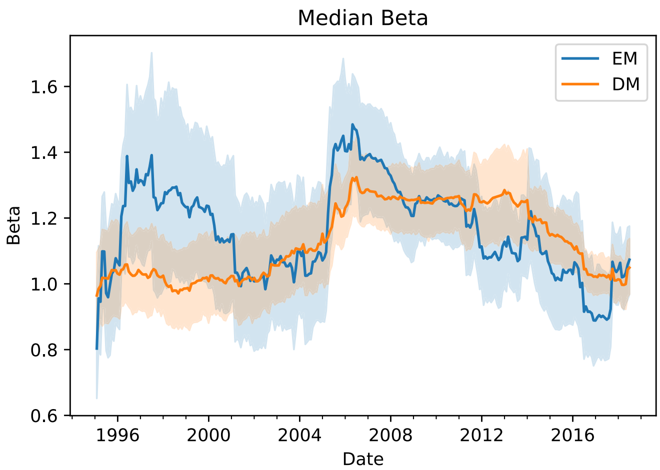




**Fig. 6.** Betas and correlations.
Five-year (centered) rolling betas and correlations by MSCI classification. Betas and correlations are with respect to DM returns (MSCI World). The lines indicate the medians for each group and the shaded region represents a 95% confidence interval on the cross-section of countries.

trend of the emerging market correlations, increasing from a very low 0.3 median correlation to over 0.7, is striking. Correlations dropped below 0.5 after the global financial crisis, but have now increased to around 0.6. Frontier markets (not shown) are slightly less correlated with the MSCI World Index than are emerging markets.

The explanation for some of the initial increases in correlations is straightforward. At the end of the 1980s and the beginning of the

**Table 6**
Risk Regressions.

| | $\rho$ | $\beta$ | Total volatility | Idiosyncratic volatility |
|---|---|---|---|---|
| Constant | 0.777*** | 1.134*** | 0.213*** | 0.126*** |
| | (0.016) | (0.032) | (0.007) | (0.007) |
| EM | −0.218*** | 0.017 | 0.093*** | 0.119*** |
| | (0.023) | (0.060) | (0.010) | (0.010) |
| Trend | 0.007*** | 0.007 | −0.001 | −0.002*** |
| | (0.001) | (0.004) | (0.001) | (0.000) |
| EM × Trend | 0.003 | −0.013 | −0.007*** | −0.007*** |
| | (0.002) | (0.008) | (0.001) | (0.001) |
| $R^2$ | 0.422 | 0.014 | 0.385 | 0.553 |

This table shows cross-sectional regressions of five-year centered rolling correlation $\rho$, $\beta$, annualized total volatility, annualized idiosyncratic volatility on an EM dummy, trend and an interaction term. The time trend variable is in years. The data sample is from 1995 to 2020 including countries classified as DM and EM in MSCI. $^{***}$,$^{**}$, and $^{*}$ indicate significance at 5%, 1%, and 0.1%, respectively.

1990s, many emerging equity markets embarked on a liberalization process, which raised their correlation with the rest of the world (see Bekaert and Harvey, 2000, and Henry, 2000). Since then, a gradual increase in correlations has made diversification benefits a more challenging rationale for investing in emerging markets. Currently, the correlation of the emerging market index with the world index is about 0.8.

The correlation between two markets can be expressed as the product of beta and the ratio of standard deviations. Using this decomposition, the increasing correlations with the world market can be the result of higher betas with respect to the world market, increases in world market volatility, or decreases in country-specific volatility. Whereas increases in global volatility may be temporary, associated with occasional global stock market crashes, changes in beta and country-specific volatility may be more permanent. The bottom panel of Fig. 6 is similar to the top panel but shows betas. The developed market betas (in orange) not surprisingly hover around 1.0, but the emerging market betas (in blue) exhibit a steep increase during the 1990s, likely associated with the liberalization process. Betas now seem to fluctuate within a 1.1–1.4 band, making emerging markets a risky, high-expected-return asset class.

Table 6 uses our rolling statistics to provide formal statistical tests on risk differences between emerging markets (EM) and developed markets (DM) and provides tests for trends. The first column ($\rho$) indicates that the average EM-to-world correlation is 0.22 lower than the correlation of a typical developed market with the world. Correlations of both developed and emerging markets with the MSCI World Index exhibit trends, but the trend for emerging markets is somewhat, but not statistically significantly, stronger. These results are consistent with some of the recent literature (see, for example, Christoffersen et al., 2012). The next column ($\beta$) in the table investigates the rolling betas, showing that emerging markets have higher betas on average than do developed markets. The differences are not significant and exhibit no significant trends.

A linear pattern has difficulty picking up the nonlinear behavior illustrated in Fig. 6, a steep increase, followed by oscillating behavior. A contribution to the higher correlations over time of a more-linear nature is the secular decrease in the volatility of emerging market returns. In Table 6, we report statistics for total volatility and idiosyncratic volatility. Country-specific volatility in emerging markets is about 9.35% higher than that of developed markets when the units are in annualized volatility and even larger at 11.80% for idiosyncratic volatility. Importantly, a downward trend in country-specific volatility exists for both groups, but the trend is stronger and statistically significant for emerging market countries. The effect is economically large, corresponding to a 0.70% decrease per year.

Correlations with the world market fluctuate with variations in betas, world volatility, and variation in idiosyncratic volatility. Thus, attributing the variance to each of these three components is informative. To this end, Appendix B derives an expression for the correlation as a linear function of these three components, which uses a Taylor series expansion of the nonlinear relation around the cross-sectional mean of the correlation. Using this linear approximation, we can compute a variance decomposition of the time variation in correlation by dividing the covariance of the correlation with each of the three components by the total correlation variance. We conduct this variance decomposition for each country in our sample and show statistics of the distribution for the developed and emerging market groups in Table 7. Panel A shows the results for the level of correlation, Panel B for changes in correlation. For the developed markets, the three components on average contribute equally to the variation in correlation. For the emerging markets, however, variation in beta is most important, followed by country-specific volatility. The dominance of beta variation is even more important for changes in correlation and is the most important component for both developed and emerging markets, but its dominance is much more prominent for emerging markets. The relative importance of country-specific volatility is small for correlation changes, perhaps reflecting that its contribution to correlation changes occurs at lower frequencies (see Table 6).

Whether emerging markets have indeed become a high-beta, risky asset class also depends on whether their exposure to world market returns is symmetric across up and down markets. If the beta decreases well below 1.0 in stressed equity markets, emerging markets offer valuable diversification benefits. Online Table A2 reports the results from a regression accommodating a "downside" beta, that is, the beta can change depending on the sign of the world market return. We find betas to increase in down markets, but the change is statistically significant only for quite extreme stress thresholds.

Up to this point, all of our computations have used, as is common in academic research, monthly data. If returns are i.i.d. over time, the use of monthly data would have little consequence, but this condition is unlikely to hold true. Investment horizons for most investors are much longer than one month, with rebalancing happening less frequently than monthly. Table 8 reports the correlations of EM countries and DM countries with the MSCI World Index (left panel) and with the US market (right panel), for longer return horizons of six months, one year, and three years. We do not go beyond the three-year horizon because the number of fully independent observations becomes too small. We use Newey–West standard errors spanning five years. To obtain estimates of correlations, we set up a GMM system with three moments per country (mean, variance, and covariance with benchmark). We then use the delta method to obtain estimates and standard errors for the average correlation in developed and emerging markets as well as their difference.

The average correlation between developed markets and the MSCI World Index is about the same at short and long horizons (0.79 vs. 0.76). For emerging markets, however, correlations fall as the horizon lengthens, decreasing from 0.55 at the one-month horizon to 0.36 at the three-year horizon. The differences between DM and EM correlations are significantly different from zero at all horizons, even at the three-year horizon, with a maximum difference of 0.4. For emerging markets relative to the US market, the decrease in correlations as the horizon lengthens is even steeper, with the average correlation dropping from 0.50 to 0.03. We also observe a small decrease in the average DM correlation with the US market, which falls from 0.70 to 0.51.

## 4. The strategic asset allocation to emerging markets

The natural starting point to determine the strategic asset allocation to emerging markets is the relative market capitalization of

**Table 7**
Correlation variance decomposition.

| | Developed ($N = 24$) | | | | Emerging ($N = 28$) | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | SD | 10% | 90% | Mean | SD | 10% | 90% |
| $var(ln\rho)$ | 0.026 | 0.025 | 0.006 | 0.049 | 0.203 | 0.187 | 0.040 | 0.347 |
| $ln\beta$ | 0.386 | 0.197 | 0.168 | 0.670 | 0.402 | 0.230 | 0.080 | 0.685 |
| $ln\sigma_f$ | 0.359 | 0.235 | 0.114 | 0.582 | 0.279 | 0.173 | 0.071 | 0.511 |
| $ln\sigma_i$ | 0.419 | 0.301 | 0.145 | 0.670 | 0.353 | 0.242 | 0.075 | 0.739 |
| $var(ln\Delta\rho)$ | 0.001 | 0.000 | 0.000 | 0.001 | 0.005 | 0.009 | 0.001 | 0.007 |
| $ln\beta$ | 0.387 | 0.042 | 0.345 | 0.432 | 0.646 | 0.071 | 0.612 | 0.706 |
| $ln\sigma_f$ | 0.370 | 0.226 | 0.154 | 0.712 | 0.183 | 0.106 | 0.065 | 0.343 |
| $ln\sigma_i$ | 0.177 | 0.115 | 0.080 | 0.369 | 0.078 | 0.061 | 0.013 | 0.137 |
| $\rho^{ss}$ | 0.758 | | | | 0.545 | | | |
| $\kappa_1$ | −0.802 | | | | −0.432 | | | |

Cross-sectional statistics of a country-level variance decomposition of $ln\rho$ and $\Delta ln\rho$ into components attributable to $\beta$, $\sigma_f$, and $\sigma_i$. The top panel calculates the variance decomposition for levels and the bottom panel for differences. The first row is the variance of the correlation of returns with respect to the DM index (MSCI World) and the next three rows are the ratio of the variance explained by that component. $\kappa_1$ is calculated as the cross-sectional average for each class. The sample of five-year centered rolling estimates is from 1995 to 2020.

**Table 8**
Average long-run correlation.

| $h$ | Benchmark: DM | | | Benchmark: US | | |
|---|---|---|---|---|---|---|
| | DM | EM | Diff | DM | EM | Diff |
| 1m | 0.793 | 0.555 | −0.237 | 0.702 | 0.498 | −0.204 |
| | (0.09) | (0.07) | (0.03) | (0.09) | (0.06) | (0.05) |
| 6m | 0.813 | 0.581 | −0.232 | 0.712 | 0.471 | −0.241 |
| | (0.14) | (0.13) | (0.05) | (0.14) | (0.13) | (0.05) |
| 1y | 0.801 | 0.531 | −0.270 | 0.682 | 0.383 | −0.299 |
| | (0.12) | (0.15) | (0.08) | (0.11) | (0.14) | (0.07) |
| 2y | 0.805 | 0.465 | −0.339 | 0.627 | 0.223 | −0.404 |
| | (0.14) | (0.22) | (0.13) | (0.10) | (0.16) | (0.15) |
| 3y | 0.755 | 0.356 | −0.400 | 0.511 | 0.032 | −0.479 |
| | (0.21) | (0.33) | (0.21) | (0.15) | (0.18) | (0.26) |

This table shows the average unconditional correlations calculated using overlapping $h$-period excess returns (eg. $corr\left(r_{t,t+h}, r^m_{t,t+h}\right)$), relative to the DM index (MSCI World) and relative to US market returns. Newey-West standard errors (shown in parentheses) are computed by GMM using the delta method and use a lag length of five years to account for the serial correlation of overlapping returns. The sample includes 21 DM and 20 EM countries with $h-$ period returns going from 1995 to 2020.

emerging market equities, but this number is hard to pin down for a variety of reasons. First, relative market capitalization differs across data providers. In 2021, for example, relative market capitalization of EM equities was 12.0% for the MSCI Emerging Market Index, but 10.3% for the FTSE Emerging Index. One reason for this disparity is the country composition of the two indices. For example, FTSE Russell classifies Korea as a developed market, but MSCI classifies it as emerging. Second, index providers such as MSCI and FTSE Russell do not count all of the market capitalization. They focus on the free float. Some market capitalization may not be readily available for transactions because, for example, it is government-held. Emerging markets have much lower proportions of free float than developed markets.[11]

Free-float adjustments likely play a role in the higher relative market capitalizations we find for other data sets. For example, when we compute the relative market capitalization based on data from DataStream, which captures a higher percentage of the market than the traditional vendors, we find a relative market capitalization of 17.5% The DataStream data mitigate one important issue in current EM indices—the high weight assigned to China. In March 2019 about one-third of the MSCI Emerging Markets Index was allocated to Chinese stocks (even though the allocation includes very few A-shares) compared to less than 15% of the DataStream index. In the same year, DataStream allocated almost 16% to India compared to just over 9% by MSCI (Table A2 shows the top nine country weights for both indices in March 2019). Fig. 7 shows how the relative EM market capitalization rose from barely 2.5% in 1999 to close to 20% around 2010, decreasing to about 17.5% in around 2015.

We use standard Jensen's regressions using excess returns to document the historical performance of EM investments relative to the

[11] In 2013, the average free float to total market capitalization for the MSCI Emerging Markets Index was 56%. In contrast, the ratio in the United States was 94%.

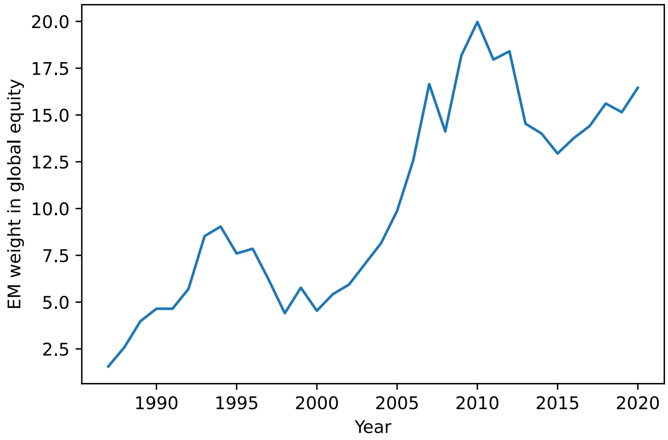



**Fig. 7.** EM relative market capitalization.
This figure shows the weight allocated to emerging market (EM) countries in a global equity value-weighted portfolio. EM weight is measured as the total equity market capitalization of EM countries relative to the World equity market capitalization. Data on equity market capitalization is from *Datastream* indices.

MSCI World index. We use the one-month US T-bill from the Kenneth R. French Data Library as the risk-free rate. We report the results in Table 9. The first two columns show average return and standard deviation and the next two columns show alpha and beta relative the MSCI World Index. Numbers in parentheses are heteroskedasticity-consistent standard errors. In addition to value weighting, we consider a number of other weighting schemes. The last set of columns reports alpha and beta with respect to the value-weighted MSCI Emerging Market Index for the alternative weighting schemes. For all these strategies, rebalancing happens once per year at year-end to minimize transaction costs.

The first row of Table 9 reports the performance of the value-weighted MSCI Emerging Market Index relative to the MSCI World Index. Our sample begins in 1995 to ensure we do not count "returns to integration" as part of expected EM performance for global investors. The performance of the emerging market index improves when the sample begins earlier. The table reveals that, consistent with our earlier results, emerging markets have a beta higher than 1.0 relative to developed markets, but the alpha is negative and not statistically different from zero. In the second row of the table, we use alternative market capitalization weights from DataStream, which does not change this conclusion.

In terms of alternative weighting schemes, the first strategy (EW) is an equal-weighted strategy across the countries in the index. Such portfolios have been shown to provide better diversification than value-weighted portfolios and are hard to beat in out-of-sample exercises in the portfolio choice literature (see DeMiguel et al., 2009). The equal-weighted portfolio incurs higher transaction costs due to the required rebalancing. The strategy has a value tilt, that is, in order to achieve equal weights at rebalancing, the strategy buys countries with recent negative returns and sells those with recent highly positive returns. A second strategy (MY), the stock market capitalization as a share of GDP, incorporates the idea there may be convergence in stock market development across time. This strategy weights the countries inversely with the market-capitalization-to-GDP ratio. The next two strategies weight countries according to valuation: one inversely proportional to PE ratios (thus, proportional to earnings yields) (PE) and the other proportional to dividend yields (DY). The procedure is simple: where $x_{t,i}$ is the country's value for the statistic (e.g., inverse of the market-cap-to-GDP ratio or the dividend yield), the weight is simply $x_{t,i}/\left(\sum_i x_{t,i}\right)$. The final strategy in this group is a GDP-weighted strategy (GDP) in which countries are weighted according to their relative end-of-year GDP. (DeMiguel et al., 2009)

Importantly, all five strategies provide positive alphas relative to the MSCI World Index, but none of the alphas are statistically significantly different from zero. The two middle columns reveal that all five strategies provide a statistically significant alpha relative to the value-weighted emerging market index. The alphas are economically large for all five strategies, ranging from 3.2% annualized for the GDP-weighted portfolio and over 4.9% annualized for both the (inverse) market cap to GDP and dividend yield strategies. Thus, a fundamental-based asset allocation strategy may be valuable for investors in the emerging markets. One possible critique is that the comparison is unfair, because presumably similar strategies could also improve the performance of the developed-market world index. We test this conjecture in Online Table A3 and find it untrue: none of the five strategies improve the performance of the MSCI World Index.

A second criticism is that these results do not account for transaction costs. To ascertain how important transaction costs may be, we compute annual turnover ratios for each strategy and report them in Table 10. Even value-weighted strategies feature transaction costs related to turnover, for example, resulting from a definition change such as stocks being removed or added to the index. Average annual turnover is only 1.2% for developed markets, but 5.3% for emerging markets. Given this "natural" turnover, the turnover in the EW and GDP strategies is particularly small at less than 10.0%, whereas the other three strategies (MY, PE, and DY) have turnover of 17–18.0%. Transaction costs, therefore, are unlikely to materially affect the magnitude of the reported alphas.

The next four rows in Table 9 report results from popular equity factor strategies, but applied at the country level. The momentum (MOM) strategy overweights countries with recent strong performance. The strategy is implemented using the sorting variable $x_{t,i} =$

**Table 9**
EM excess return statistics, 1995–2020.

| Portfolios | $\mu$ | $\sigma$ | DM | | EM | |
|---|---|---|---|---|---|---|
| | | | $\beta$ | $\alpha$ | $\beta$ | $\alpha$ |
| MSCI EM | 6.63 | 22.34 | 1.20 | −1.62 | – | – |
| | (4.39) | | (0.06) | (2.72) | – | – |
| VW | 7.20 | 23.04 | 1.23 | −1.28 | 1.01 | 0.51 |
| | (4.52) | | (0.06) | (2.73) | (0.01) | (0.91) |
| EW | 9.48 | 21.88 | 1.15 | 1.58 | 0.93 | 3.20 |
| | (4.29) | | (0.06) | (2.70) | (0.02) | (1.33) |
| MY | 11.40 | 23.75 | 1.19 | 3.18 | 0.98 | 4.93 |
| | (4.66) | | (0.07) | (3.09) | (0.03) | (1.88) |
| PE | 10.48 | 22.40 | 1.15 | 2.56 | 0.94 | 4.24 |
| | (4.39) | | (0.06) | (2.87) | (0.02) | (1.53) |
| DY | 10.87 | 21.62 | 1.10 | 3.29 | 0.90 | 4.92 |
| | (4.24) | | (0.06) | (2.80) | (0.03) | (1.61) |
| GDP | 10.08 | 23.73 | 1.24 | 1.56 | 1.03 | 3.23 |
| | (4.65) | | (0.06) | (3.15) | (0.01) | (1.06) |
| MOM | 8.57 | 22.05 | 1.12 | 0.84 | 0.92 | 2.51 |
| | (4.32) | | (0.06) | (2.88) | (0.03) | (1.67) |
| REV | 10.39 | 22.63 | 1.18 | 2.29 | 0.95 | 4.10 |
| | (4.44) | | (0.06) | (2.79) | (0.02) | (1.56) |
| IR | 8.46 | 20.60 | 1.09 | 0.97 | 0.88 | 2.61 |
| | (4.04) | | (0.06) | (2.51) | (0.02) | (1.19) |
| BETA | 8.60 | 20.50 | 1.04 | 1.41 | 0.86 | 2.89 |
| | (4.02) | | (0.06) | (2.67) | (0.02) | (1.42) |
| GDPexCHN | 10.38 | 24.65 | 1.29 | 1.47 | 1.05 | 3.44 |
| | (4.84) | | (0.06) | (3.00) | (0.02) | (1.53) |
| VWexCHN | 6.95 | 23.34 | 1.25 | −1.63 | 1.01 | 0.24 |
| | (4.58) | | (0.06) | (2.83) | (0.02) | (1.18) |

Excess return statistics of alternative EM portfolios from 1995 to 2020. The portfolio weights are value-weighted using Datastream market capitalization (VW), equally-weighted (EW), the inverse of market value to GDP (MY), inverse of price-to-earnings (PE), dividend yield (DY), GDP in constant dollars (GDP), one-year momentum (MOM), one-year return reversal (REV), World Beta (BETA), and idiosyncratic risk relative to World market (IR) (see text for details). The last two portfolios are GDP-weighted and market value-weighted excluding China. Portfolios are constructed using annual rebalancing. Return statistics and alphas are annualized and expressed in percentage points (%). Numbers in parentheses are Heteroskedasticity-consistent standard errors.

**Table 10**
Portfolio Turnover.

| | Average Annual Turnover % | |
|---|---|---|
| Portfolio | EM | DM |
| VW | 5.3 | 1.2 |
| EW | 9.5 | 5.2 |
| MY | 17.6 | 10.0 |
| PE | 17.9 | 10.9 |
| DY | 18.0 | 9.7 |
| GDP | 9.4 | 4.1 |
| MOM | 30.9 | 23.8 |
| REV | 33.5 | 29.2 |
| BETA | 14.0 | 11.6 |
| IR | 13.0 | 8.5 |

Average (annual) portfolio turnover for alternative strategies. Turnover is measured as $Turnover = \frac{1}{T-1}\sum_t\sum_i \frac{|w_{i,t} - w_{i,t-1}R_{i,t}/R_{p,t}|}{2}$, where $w_{i,t}$ and $R_{i,t}$ are country $i$'s weight and return, respectively, and $R_{p,t}$ is the portfolio's return in month $t$. This formula accounts for valuation effects on portfolio holdings. Portfolios are constructed using annual end-of-year rebalancing. The sample is from 1995 to 2020.

$r_{t,i} - min(r_{t,j})$, where returns are annual returns over the preceding calendar year. The reversal (REV) strategy uses the sorting variable $max(r_{t,j}) - r_{t,i}$, which relatively overweights underperforming countries over the preceding calendar year. We also analyze a betting-against-beta (BETA) strategy, using $max(\beta_{t,j}) - \beta_{t,i}$, where $\beta$ is computed as the slope coefficient of rolling regressions with respect to the return of the MSCI World Index over the previous three calendar years (backward-looking, rolling window). The fourth factor-inspired strategy we study is the betting-against-high-idiosyncratic-risk (IR) strategy, using $max(ivol_{t,j}) - ivol_{t,i}$, where *ivol* is the standard deviation of the residuals in the regression used in the BETA strategy.

All four strategies (MOM, REV, BETA, and IR) provide alpha relative to the MSCI World Index, but again the alpha is not statistically significantly different from zero. Three of the four strategies, with the exception being the MOM strategy, provide significant alpha relative to the MSCI Emerging Markets Index. In the emerging markets, the MOM and REV strategies have average annual turnover of over 30% (see Table 10). Online Table A3 shows that these strategies, as we implement them in our analysis with annual rebalancing, do not provide significant alpha in the developed markets. In unreported results, however, we find that they perform better in the developed markets using monthly rebalancing.

The last two rows of Table 9 highlight China's performance contribution to an EM portfolio; recall that China is currently the largest market in the MSCI Emerging Markets Index. The last row (VWexCHN) reports results for the value-weighted index minus China. The performance relative to the MSCI World Index is almost identical to the performance of the index itself. Not surprisingly, the "China-less" strategy shows only a small and insignificant positive alpha relative to the MSCI Emerging Markets Index. The next to last line recomputes the GDP strategy excluding China (GDPexCHN), which has a dominant weight in the GDP portfolio. The performance of GDPexCHN is almost indistinguishable from the performance of the GDP strategy. We conclude that standard emerging market indices have not provided alpha in the past, but that alternative weighting schemes may provide alpha relative to the MSCI World Index. The results are noisy, but even a small alpha (after factoring in transactions costs) can provide good motivation for additional allocation by investors to emerging markets. Assuming that the emerging market index constitutes 15% of total market capitalization, an alpha of only 50 bps would increase the allocation to 23%.[12]

An alternative argument for increasing the allocation to emerging markets relative to market-capitalization weights is the low correlations over longer horizons that we documented earlier. Imagine that equity prices are set mostly by relatively short-horizon investors and that we can reverse engineer expected returns from market capitalizations and a short-term covariance matrix. These expected returns would reflect the market equilibrium, and short-term investors thus would allocate capital to emerging markets in line with their relative market capitalization. In contrast, given their longer investment horizons, institutional investors should set their strategic asset allocation consistent with the market's expected returns, but use the long-term covariance matrix. When we attempt such an exercise we find the lower long-term correlations come with higher long-term volatilities, rendering a minimal impact on the optimal asset allocation.

Of the various weighting schemes we examined in our analysis, GDP is likely the one most alluded to among practitioners, because emerging markets are substantially underrepresented in terms of market capitalization relative to their share of GDP. Should we expect this gap to close eventually? We do not believe the gap between the relative weight of emerging markets in terms of market cap versus their much higher weight in terms of GDP is a good reason to overweight emerging markets. Such a gap is no guarantee of out-performance, because share issuance is the most likely way the gap will close, and we do not observe convergence in these market capitalization to GDP ratios (see results in Table 2). Finally, GDP weights greatly increase the concentration of the emerging market index in China and in the BRICs.

Our results in Table 9 show that the within-EM GDP strategy leads to a significant alpha relative to the value-weighted emerging market index. The results also show that alternative weighting schemes, including valuation-based weighting and weights based on the inverse of the market-cap-to-GDP ratio, provide higher alphas. This makes sense because Table 2 also shows that valuation convergence has not completely eliminated the emerging market discount. Thus, some of the gap between relative market capitalization and relative GDP weights may be eliminated by further valuation convergence. Our results suggest that using these valuation differentials in a fundamental-based tactical asset allocation strategy may add value within emerging markets and may also add value when applied across all DM and EM markets (which we defer to future research).

## 5. The case for emerging markets revisited

We summarize our main findings as follows. Emerging equity markets differ in a statistically significant way from developed markets, featuring much lower levels of GDP per capita and *de jure* levels of equity integration. They also have significantly lower equity-market development levels as measured by the ratio of market capitalization to GDP and, on average, feature lower valuation ratios. Although convergence of emerging markets to developed market levels is slowly occurring in GDP and more rapidly for valuation measures, the other development indicators we study have not changed much over the last 20 to 25 years. Therefore, we believe emerging markets should still be viewed as a separate asset class. We show that the largest emerging markets would be more logically categorized as frontier markets when the deviations of the development indicators relative to developed markets are aggregated and ranked relative to other emerging and frontier markets. That is, many MSCI frontier markets rank much higher in our objective criteria (including GDP per capita and market capitalization to GDP) than do major MSCI emerging markets such as China and Brazil.

Kritzman (1999) defined an asset class as a set of homogenous securities (with similar properties) and enough capacity to accommodate large investments. These two properties are still satisfied for emerging markets. Kritzman also argued that an asset class should show sufficiently low correlation with existing asset classes and ultimately raise portfolio utility.

[12] These computations assume expected returns are consistent with the relative market capitalization and use the full sample covariance matrix. We consider 100% equity portfolios.

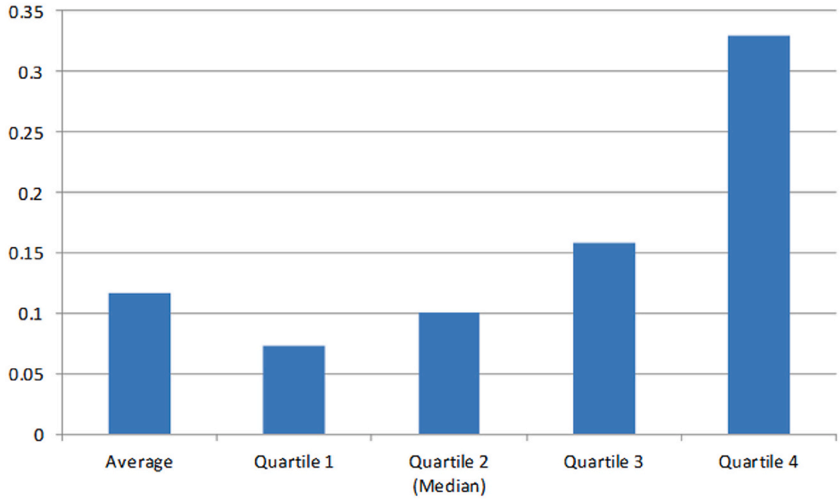



**Fig. 8.** Emerging Equity Market Exposure of Institutional Investors in 2011.
(Source: MSCI survey of 85 institutional investors.)

At first blush, some recent developments have made emerging markets less attractive investments and a less obvious asset class. Globalization has increased country return correlations with the developed markets. Not only have valuations somewhat converged (see Bekaert et al., 2011), but after the capital market liberalization process of the late 1980s and early 1990s, the correlation between emerging and developed market returns has substantially increased. Decomposing the correlation into a beta and a volatility ratio, we find that a good part of the increase in correlation is associated with the higher beta of the emerging market index, making emerging market investments a high-expected-return asset, but also a risky asset. An investment in an individual country is quite volatile. The average volatility of an EM country is more than 10 percentage points higher than the volatility of a DM country, but an active asset manager seeks high volatility. High volatility and unique country factors create opportunities for outperformance. For example, the best and worst performing equity markets since 1990 have been, in more than 90% of cases, emerging markets.

Despite high country-specific volatility, a diversified basket of emerging markets is not overly volatile, having about the same volatility as a typical large developed market. Bekaert et al. (2011) not only showed that the globalization process led to some valuation convergence, but also that the process is far from smooth. Valuation convergence in itself may provide opportunities for excess returns from global tactical asset allocation programs. Finally, return correlations of emerging markets with developed markets appear smaller over longer investment horizons.

From a passive investment perspective, the case for emerging markets as a valuable addition to developed market portfolios has become less obvious. In fact, we show that value-weighted EM indices have delivered negative alpha relative to the MSCI World Index since 1995. We find, however, that some alternative weighting schemes can provide positive alphas, but they are not significantly different from zero. Equal-weighted indices have fared much better and we show that weighting countries inversely to their market-capitalization-to-GDP ratio and by valuation ratio are valuable strategies and generate positive alphas.

An approach gaining popularity weighs emerging markets according to their relative share of GDP, thus overweighting emerging markets in strategic asset allocations. The share of world output accounted for by emerging markets is indeed far greater than their share of equity market capitalization. No evidence exists, however, that market- capitalization-to-GDP ratios are converging across emerging and developed markets. GDP-weighted indices would worsen concentration issues in most popular emerging market indices, increasing the share of the larger emerging markets such as Brazil, India, and most importantly China, which represents over 30% of both the MSCI and FTSE emerging market indices. Whereas we show that GDP-weighted portfolios outperform value-weighted EM indices, valuation-based weighting strategies fare even better.

Therefore, a strategic allocation between market-capitalization weights and GDP weights may be justified. Institutional investors, however, still appear to be underweight in emerging markets. In 2011, MSCI conducted a global survey of asset allocation and risk management practices of institutional investors (see Fig. 8). The 85 participants included 35 public plans, 16 corporate plans, 10 endowments/foundations or sovereign wealth funds, and 24 unclassified institutions. The average allocation to emerging markets was well below 15%, less than the market-capitalization weight of emerging markets in the world markets. Considerable dispersion existed across institutions, with some investors allocating over 30% to emerging markets. The MSCI survey also identified a general trend toward decreased allocations to developed domestic equities and toward increased exposures to emerging market equities. Based on the results of our research, we expect the trend to continue. More recent data show that the equity allocation for US endowments as of 2020 had a dedicated EM allocation of only 7.75%.[13] However, as a fraction of the total of US, non-US DM and EM allocations (that is, dropping non-public equity and global allocations), the emerging market allocation represented 22.74%.

[13] Only data on US institutions were available to us. Their full equity allocation, dominated by alternatives, is in Online Table A5.

Our findings have important implications for investment managers and are particularly relevant for large institutional investors such as pension funds and insurance companies. Although we focus our analysis on equities, corporate and sovereign bonds as well as investable currencies now offer a wide range of available investment opportunities for developed market investors in emerging markets. We defer studying these asset classes to future work, but any asset allocation to emerging markets should now include such relatively new assets.

## Data availability

Data will be made available on request.

## Appendix A. Risk and return

Table 5 presents return summary statistics for DM and EM index returns. Panel A shows estimates for the DM index (MSCI World) and the EM index (MSCI EM), while panel B shows statistics for an equal-weighted index. In panel A and B the statistics of interest are average return $\mu_i$, standard deviation $\sigma_i$, skewness $s_i$, and kurtosis $k_i$. The moment conditions are

$$\begin{aligned}
0 &= E\left(X_{i,t} - \mu_i\right) \\
0 &= E\left(X_{i,t}^2 - \mu_i^2 - \sigma_i^2\right) \\
0 &= E\left(X_{i,t}^3 - s_i\sigma_i^3 + 4\mu_i\sigma_i^2 + \mu_i^3\right) \\
0 &= E\left(X_{i,t}^4 - k_i\sigma_i^4 + 4s_i\sigma_i^3\mu_i + 6\sigma_i^2\mu_i^2 + \mu_i^4\right)
\end{aligned}$$

where $i \in \{DM, EM\}$ so in total we have 8 moments. We can then use the Delta method to get the standard errors of $\mu_i, \sigma_i, s_i, k_i$.

For panel C we calculate statistics of the cross-section of country returns. This requires a system of moments for individual countries as well as for an equally-weighted index. The first four statistics are:

$$\overline{\mu}_{EM} = \frac{1}{N}\sum_i \mu_i, \qquad \overline{\sigma}_{EM} = \frac{1}{N}\sum_i \sigma_i$$

$$\overline{s}_{EM} = \frac{1}{N}\sum_i s_i, \qquad \overline{k}_{EM} = \frac{1}{N}\sum_i k_i$$

The other statistics of interest are the average covariance between EM country returns ($\overline{Cov}_{EM}$), and the *volatility-weighted* average correlation ($\overline{\rho}_{EM}$):

$$\begin{aligned}
\overline{Cov}_{EM} &= \frac{2}{N(N-1)}\sum_i\sum_{j\neq i}\sigma_{ij} = \frac{N}{N-1}Var\left(\frac{1}{N}\sum_i r_{i,t}\right) - \frac{1}{N(N-1)}\sum_i \sigma_i^2 \\
\overline{\rho}_{EM} &= \frac{2}{N(N-1)}\sum_i\sum_{j\neq i} w_{i,j}\frac{\sigma_{ij}}{\sigma_i\sigma_j} = \frac{N(N-1)}{2}\frac{\overline{Cov}_{EM}}{\sum_i\sum_{j\neq i}\sigma_i\sigma_j}
\end{aligned}$$

where the weighting is

$$w_{i,j} = \frac{\sigma_i\sigma_j}{\frac{2}{N(N-1)}\sum_i\sum_{j\neq i}\sigma_i\sigma_j}$$

The advantage of using a volatility-weighted average correlation is that we can obtain the statistic and standard errors in a GMM system using individual country and equal weighted index moments, obviating the need to calculate all the cross-correlations.

In addition to the moment conditions from panels A and B, panel C has:

$$0 = E\left(\frac{1}{N}\sum_i X_{i,t}^m - \overline{\mu}_m\right)$$

$$0 = E\left(\left(\frac{1}{N}\sum_i X_{i,t}^m\right)^2 - \overline{\mu}_m^2 - \overline{\sigma}_m^2\right)$$

where $i$ are individual countries in $m \in \{DM, EM\}$. Therefore, we have two moments per country and two moments for the equal-weighted index returns of each class. To facilitate estimation we only include countries with data available from 1995 to 2020. In total, this means we have $2N_{DM} + 2N_{EM} + 4 = 84$ moments. We then use the Delta method to get the standard errors of the statistics of interest. For example, $\overline{Cov}_{EM}$ and $\overline{\rho}_{EM}$ are functions of $\overline{\sigma}_{EM}^2$ and the individual $\sigma_i$'s.

## Appendix B. Correlation decomposition

To study the drivers of correlation changes, we decompose correlation into beta ($\beta$), factor volatility ($\sigma_f$) and idiosyncratic volatility ($\sigma_{x,i}$). Start with the following formula that:

$$\rho = \beta\frac{\sigma_f}{\sigma_x} = \beta\frac{\sigma_f}{\sigma_{x,i}}\frac{\sigma_{x,i}}{\sigma_x}$$

Since the ratio of idiosyncratic volatility to total volatility is

$$\frac{\sigma_{x,i}}{\sigma_x} = \sqrt{1-\beta^2\frac{\sigma_f^2}{\sigma_x^2}}$$

Using log-linear approximation around the cross-sectional average $\rho_{ss}$,

$$ln\left(\frac{\sigma_{x,i}}{\sigma_x}\right) \approx \kappa_0 + \kappa_1 ln\rho$$

Using $f(x) \approx f(x^*) + f'(x^*)(x - x^*)$

$$\begin{aligned} ln\left(\frac{\sigma_{x,i}}{\sigma_x}\right) &= 0.5ln\left(1-e^{2ln\rho}\right) \\ &\approx 0.5ln\left(1-\rho_{ss}^2\right) - \frac{\rho_{ss}^2}{1-\rho_{ss}^2}(ln\rho - ln\rho_{ss}) \\ &\approx 0.5ln\left(1-\rho_{ss}^2\right) + \frac{\rho_{ss}^2}{1-\rho_{ss}^2}ln\rho_{ss} - \frac{\rho_{ss}^2}{1-\rho_{ss}^2}ln\rho \end{aligned}$$

So

$$\kappa_0 = 0.5ln\left(1-\rho_{ss}^2\right) + \frac{\rho_{ss}^2}{1-\rho_{ss}^2}ln\rho_{ss}$$

$$\kappa_1 = -\frac{\rho_{ss}^2}{1-\rho_{ss}^2}$$

Then,

$$\begin{aligned} (1-\kappa_1)ln\rho &= \kappa_0 + ln\beta + ln\sigma_f - ln\sigma_{x,i} \\ (1-\kappa_1)\Delta ln\rho &= \Delta ln\beta + \Delta ln\sigma_f - \Delta ln\sigma_{x,i} \end{aligned}$$

It follows that the variance decomposition of $ln\rho$ and $\Delta ln\rho$ is

$$\frac{1-\kappa_1}{\kappa_0} = \left(\frac{cov(ln\rho, ln\beta)}{var(ln\rho)} + \frac{cov\left(ln\rho, ln\sigma_f\right)}{var(ln\rho)} - \frac{cov\left(ln\rho, ln\sigma_{x,i}\right)}{var(ln\rho)}\right)$$

and

$$1-\kappa_1 = \left(\frac{cov(\Delta ln\rho, \Delta ln\beta)}{var(\Delta ln\rho)} + \frac{cov\left(\Delta ln\rho, \Delta ln\sigma_f\right)}{var(\Delta ln\rho)} - \frac{cov\left(\Delta ln\rho, \Delta ln\sigma_{x,i}\right)}{var(\Delta ln\rho)}\right)$$

In Table 7 we calculate $\kappa_1$ as the cross-sectional average for each class.

## Appendix C. List of countries

Argentina (ARG), Australia (AUS), Austria (AUT), Bahrain (BHR), Belgium (BEL), Brazil (BRA), Bulgaria (BGR), Canada (CAN), Chile (CHL), China (CHN), Colombia (COL), Czech Republic (CZE), Denmark (DNK), Egypt (EGY), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hong Kong (HKG), Hungary (HUN), India (IND), Indonesia (IDN), Ireland (IRL), Israel (ISR), Italy (ITA), Japan (JPN), Korea (KOR), Kuwait (KWT), Malaysia (MYS), Mexico (MEX), Morocco (MAR), Netherlands (NLD), New Zealand (NZL), Nigeria (NGA), Norway (NOR), Oman (OMN), Pakistan (PAK), Peru (PER), Philippines (PHL), Poland (POL), Portugal (PRT), Qatar (QAT), Russia (RUS), Singapore (SGP), Slovenia (SVN), South Africa (ZAF), Spain (ESP), Sri Lanka (LKA), Sweden (SWE), Switzerland (CHE), Thailand (THA), Turkey (TUR), United Arab Emirates (ARE), United Kingdom (GBR), United States (USA), Venezuela (VEN), Vietnam (VNM).

## Appendix D. Appendix tables

**Table A1**
Aggregate rankings, weighted average.

| | 2000 | | | 2015 | | |
|---|---|---|---|---|---|---|
| Country | MSCI | Score | Rank | MSCI | Score | Rank |
| JPN | DM | 1.13 | 1 | DM | −0.22 | 19 |
| CHE | DM | 0.92 | 2 | DM | 0.45 | 6 |
| HKG | DM | 0.57 | 3 | DM | 0.46 | 5 |
| NOR | DM | 0.43 | 4 | DM | 0.80 | 2 |
| FIN | DM | 0.40 | 5 | DM | −0.14 | 15 |
| DNK | DM | 0.38 | 6 | DM | 0.66 | 3 |
| SWE | DM | 0.36 | 7 | DM | 0.30 | 7 |
| GBR | DM | 0.34 | 8 | DM | 0.15 | 10 |
| NLD | DM | 0.28 | 9 | DM | 0.22 | 9 |
| IRL | DM | 0.21 | 10 | DM | 0.81 | 1 |
| USA | DM | 0.07 | 11 | DM | 0.62 | 4 |
| SGP | DM | 0.02 | 12 | DM | 0.24 | 8 |
| CAN | DM | −0.06 | 13 | DM | 0.10 | 11 |
| DEU | DM | −0.07 | 14 | DM | −0.60 | 21 |
| FRA | DM | −0.10 | 15 | DM | −0.06 | 13 |
| ITA | DM | −0.24 | 16 | DM | −0.19 | 18 |
| BEL | DM | −0.25 | 17 | DM | 0.09 | 12 |
| AUT | DM | −0.28 | 18 | DM | −0.55 | 20 |
| ESP | DM | −0.71 | 19 | DM | −0.70 | 22 |
| NZL | DM | −0.96 | 20 | DM | −0.10 | 14 |
| PRT | DM | −1.01 | 21 | DM | −2.00 | 29 |
| GRC | EM | −1.06 | 22 | EM | −2.22 | 31 |
| KOR | EM | −1.22 | 23 | EM | −1.30 | 24 |
| ISR | EM | −1.24 | 24 | DM | −0.18 | 17 |
| AUS | DM | −1.43 | 25 | DM | −0.16 | 16 |
| CZE | EM | −1.89 | 26 | EM | −1.85 | 28 |
| ARG | EM | −2.37 | 27 | FM | −3.24 | 37 |
| TUR | EM | −2.43 | 28 | EM | −3.63 | 41 |
| COL | EM | −3.33 | 29 | EM | −4.17 | 44 |
| VEN | EM | −3.52 | 30 | NA | NA | NA |
| HUN | EM | −3.58 | 31 | EM | −1.39 | 25 |
| PER | EM | −3.68 | 32 | EM | −2.65 | 35 |
| MEX | EM | −3.75 | 33 | EM | −3.28 | 38 |
| EGY | EM | −3.91 | 34 | EM | −4.45 | 47 |
| SVN | FM | −3.95 | 35 | FM | −2.26 | 32 |
| MYS | EM | −4.29 | 36 | EM | −3.39 | 40 |
| CHL | EM | −4.59 | 37 | EM | −2.58 | 34 |
| ZAF | EM | −4.71 | 38 | EM | −4.10 | 43 |
| POL | EM | −4.78 | 39 | EM | −3.35 | 39 |
| BRA | EM | −5.25 | 40 | EM | −4.43 | 46 |
| THA | EM | −5.47 | 41 | EM | −4.64 | 48 |
| MAR | EM | −5.84 | 42 | FM | −5.01 | 51 |
| IDN | EM | −6.01 | 43 | EM | −4.74 | 49 |
| PHL | EM | −6.08 | 44 | EM | −5.37 | 52 |
| RUS | EM | −6.32 | 45 | EM | −3.91 | 42 |
| PAK | EM | −7.00 | 46 | FM | −6.81 | 56 |
| CHN | EM | −7.07 | 47 | EM | −4.76 | 50 |
| LKA | EM | −7.23 | 48 | FM | −5.40 | 53 |
| IND | EM | −7.85 | 49 | EM | −6.15 | 54 |
| BHR | FM | NA | NA | FM | −2.73 | 36 |
| BGR | FM | NA | NA | FM | −2.42 | 33 |
| KWT | FM | NA | NA | FM | −1.63 | 27 |
| NGA | FM | NA | NA | FM | −4.35 | 45 |
| OMN | FM | NA | NA | FM | −2.09 | 30 |
| QAT | FM | NA | NA | EM | −0.79 | 23 |
| ARE | FM | NA | NA | EM | −1.48 | 26 |
| VNM | FM | NA | NA | FM | −6.17 | 55 |

The aggregate ranking is calculated as the weighted average of z-scores relative to DM for (1) log GDP per capita, (2) equity integration, (3) MV-to-GDP, and (4) price-to-earnings ratio. The weights are 0.4, 0.3, 0.15 and 0.15, respectively. MSCI refers to the MSCI market classification. Score is distance between Emerging Market characteristics and Developed Markets as measured by the sum of $z$-score using DM mean and standard deviation for each characteristic.

To test whether emerging markets have a higher exposure to periods of higher stress, we run the following regression:

$$r_{EM,t} = \alpha_0 + \alpha_1 \cdot 1_{r_{DM,t}<k} + \beta_0 r_{DM,t} + \beta_1 \cdot 1_{r_{DM,t}<k} \cdot r_{DM,t} + \varepsilon_{EM,t}$$

where $r_{j,t}, j = EM, DM$ represents the EM (DM) excess return, and $k$ represents the threshold return. We consider threshold developed market returns to define down markets ranging from 0% to â˘6%. In the last case (< 6%), only 26 observations remain, potentially undermining the power of the regression. We report these thresholds and the average DM returns below the threshold in the left-most columns of Table A2. We also report the average EM index return below this threshold. In every case, the return is lower than the corresponding average DM return, indicating that emerging markets do not provide relief in bad times. In fact, the $\beta_1$ coefficient in the regression is invariably positive, suggesting higher betas in bad times, with the coefficient large (0.56) and highly statistically significant for $k = 6\%$, but not significant for the other thresholds. Counteracting this beta effect for the constant term is a positive interaction effect, with $\alpha_1$ positive, but the coefficient is never statistically significant. The right-most columns report returns from the same regressions using an equal-weighted emerging market index. The results are qualitatively the same, with statistical significance appearing for the lower two thresholds for both $\alpha_1$ and $\beta_1$.

**Table A2**
Downside beta and alpha.

| | | DM | EM Index | | | | | EM Equal-Weighted | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $k$ | Obs | Avg Ret | Mean | $\alpha_0$ | $\alpha_1$ | $\beta_0$ | $\beta_1$ | Mean | $\alpha_0$ | $\alpha_1$ | $\beta_0$ | $\beta_1$ |
| All months | 312 | 0.574 | 0.552 | −0.135 | | 1.198 | | 0.763 | 0.101 | | 1.154 | |
| | | | | (−0.63) | | (24.59) | | | (0.47) | | (23.63) | |
| $r < 0\%$ | 117 | −3.723 | −4.572 | 0.147 | 0.102 | 1.104 | 0.191 | −4.022 | −0.003 | 0.670 | 1.154 | 0.105 |
| | | | | (0.34) | (0.15) | (10.12) | (1.27) | | (−0.01) | (0.98) | (10.54) | (0.70) |
| $r < -2\%$ | 73 | −5.336 | −6.491 | −0.006 | 0.744 | 1.139 | 0.216 | −5.699 | −0.028 | 1.721 | 1.162 | 0.223 |
| | | | | (−0.02) | (0.83) | (12.97) | (1.36) | | (−0.09) | (1.93) | (13.24) | (1.40) |
| $r < -4\%$ | 36 | −7.906 | −9.913 | 0.024 | 1.636 | 1.127 | 0.337 | −8.714 | 0.119 | 5.192 | 1.119 | 0.655 |
| | | | | (0.10) | (0.92) | (15.64) | (1.53) | | (0.47) | (2.94) | (15.66) | (2.99) |
| $r < -6\%$ | 26 | −8.995 | −10.943 | −0.077 | 4.649 | 1.160 | 0.565 | −10.146 | 0.154 | 7.809 | 1.109 | 0.904 |
| | | | | (−0.32) | (1.89) | (17.41) | (2.11) | | (0.64) | (3.21) | (16.79) | (3.41) |

This table shows average monthly *excess* returns and downside beta coefficients for the EM MSCI index and EM equal-weighted index. The regression is: $r_{EM,t} = \alpha_0 + \alpha_1 (r_{DM,t} < k) + \beta_0 r_{DM,t} + \beta_1 (r_{DM,t} < k) r_{DM,t} + \varepsilon_{EM,t}$. All betas are calculated with respect to MSCI DM index (MSCI World) for the sample from 1995 to 2020. Alpha estimates are monthly. Numbers in parentheses are $t-$ statistics.

**Table A3**
DM excess return statistics, 1995–2020.

| | | | DM | |
|---|---|---|---|---|
| Portfolios | $\mu$ | $\sigma$ | $\beta$ | $\alpha$ |
| MSCI DM | 6.89 | 15.18 | – | – |
| | (2.98) | | – | – |
| EM | 6.63 | 22.37 | 1.20 | −1.62 |
| | (4.39) | | (0.06) | (2.72) |
| VW | 6.77 | 15.32 | 1.01 | −0.17 |
| | (3.01) | | (0.00) | (0.13) |
| EW | 7.11 | 17.78 | 1.12 | −0.57 |
| | (3.49) | | (0.03) | (1.19) |
| MY | 7.13 | 18.45 | 1.12 | −0.57 |
| | (3.62) | | (0.04) | (1.60) |
| PE | 7.27 | 18.12 | 1.13 | −0.51 |
| | (3.55) | | (0.03) | (1.29) |
| DY | 7.12 | 18.11 | 1.13 | −0.63 |
| | (3.55) | | (0.03) | (1.30) |
| GDP | 6.71 | 15.80 | 1.03 | −0.41 |
| | (3.10) | | (0.01) | (0.35) |
| MOM | 7.95 | 17.70 | 1.10 | 0.39 |
| | (3.47) | | (0.03) | (1.36) |
| REV | 6.13 | 18.21 | 1.14 | −1.68 |
| | (3.57) | | (0.03) | (1.23) |
| IR | 7.09 | 17.14 | 1.08 | −0.35 |
| | (3.36) | | (0.03) | (1.10) |
| BETA | 7.20 | 16.84 | 1.05 | −0.06 |
| | (3.30) | | (0.02) | (1.10) |

Excess return statistics of alternative DM portfolios from 1995 to 2020. The portfolio weights are value-weighted using Datastream market capitalization (VW), equally-weighted (EW), the inverse of market value to GDP (MY), inverse of price-to-earnings (PE), dividend yield (DY), GDP in constant dollars (GDP), one-year momentum (MOM), one-year return reversal (REV), World Beta (BETA), and idiosyncratic risk relative to World market (IR) (see text for details). Portfolios are constructed using annual rebalancing. Return statistics and alphas are annualized and expressed in percentage points (%). Numbers in parentheses are Heteroskedasticity-consistent standard errors.

**Table A4**
EM indices, 2019.

| Country | MSCI | DS MV |
|---|---|---|
| Total MV (million USD) | | 11,703.13 |
| China | 33.0% | 13.8% |
| Korea | 13.0% | 9.1% |
| Taiwan | 11.4% | 7.8% |
| India | 9.2% | 16.0% |
| Brazil | 7.2% | 9.0% |
| South Africa | 5.9% | 3.6% |
| Russia | 3.8% | 6.2% |
| Mexico | 2.7% | 3.3% |
| Thailand | 2.3% | 3.5% |
| Other | 11.6% | 27.9% |

Emerging market indices comparison. MSCI EM index top nine country weights in March 2019 compared to market capitalization weights from Datastream source.

**Table A5**
Equity allocations for U.S. Higher Education Endowments, 2020.

| Class | Allocation % |
|---|---|
| Dedicated US | 16.8 |
| Dedicated DM non-US | 9.5 |
| Dedicated EM | 7.8 |
| Global | 9.7 |
| Private Equity | 12.2 |
| Venture Capital | 17.8 |
| Alternatives | 26.3 |

This table shows Fiscal Year 2020 Equity Allocations for U.S. Higher Education Endowments and Affiliated Foundations. Source: 2020 NACUBO-TIAA Study of Endowments.

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