The best of both worlds: Accessing emerging economies by investing in developed markets*

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ABSTRACT

In many countries public equity markets capture a small fraction of economic activity. We show that relying on public equity indices to assess benefits from international diversification significantly understates diversification gains. We propose a new diversification approach to access a foreign country's overall economy rather than just its equity index. With this approach, we show that diversifying into emerging economies by investing solely in publicly-traded export-oriented firms in developed markets provides benefits beyond those available through emerging market equity indices. Our method delivers factor-adjusted returns above 7% annually, generates Sharpe ratios exceeding those of equity indices in developed and emerging markets, offers distinct correlation benefits, and shifts the efficient frontier by an economically large magnitude. Our results suggest that developed markets, by providing access to emerging economies, still offer substantial diversification benefits.

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International diversification is crucial to asset pricing and portfolio management. To analyze the potential benefits of investing abroad, researchers rely on foreign equity market indices. That is, they focus on the subset of firms that are publicly traded.[1] This approach can significantly understate potential diversification gains because publicly listed firms account for only a small share of the overall economy in many countries. The drawback is particularly acute for emerging countries, where, despite rapid economic growth, the stock markets have remained small relative to the size of the economy (see Bekaert and Harvey, 2014, and Figure 1). For example, just 81 firms are publicly listed in Morocco, providing a narrow window to access the economy. Even in the largest emerging economy, China, the stock markets play a relatively small role. The free-float value of Chinese markets is a third of gross domestic product, whereas it exceeds 100% in developed economies.[2]

In this paper, we propose to diversify into emerging countries via a new route – one that targets the countries' overall economies rather than just their equity indices. At the root of our "economic diversification" is the simple idea that investing in developed market firms that export to an emerging country provides exposure to economic activity of that country. For example, investing in public Australian companies that export iron ore to Indonesia can offer exposure to Indonesian infrastructure projects. We show that this approach delivers diversification benefits not attainable by investing only in publicly traded emerging market firms.

Accessing emerging economies uniquely through developed markets is also attractive because it mitigates the myriad of challenges and costs of investing directly in emerging markets (e.g., Karolyi, 2015). First, the depth of emerging equity markets is too small for large investors to achieve full benefits of diversification (Lesmond, 2005). Second, weak shareholder rights, political instability, lack of legal protection, and deficiencies in accounting standards present significant challenges for investors (Carrieri, Chaieb, and Errunza, 2013; Chuhan,

[1] A vast literature has explored various dimensions of international diversification, including identifying its sources, quantifying benefits, exploring time variation, studying the propensity of different investors to engage in it, and designing new econometric methods. See Grubel (1968), Levy and Sarnat (1970), Solnik (1974), Errunza (1977), Chan, Karolyi, and Stulz (1992), Ferson and Harvey (1994), Heston and Rouwenhorst (1994), Chang, Eun, and Kolodny (1995), Longin and Solnik (1995), Kang and Stulz (1997), Shawky, Kuenzei, and Mikhail (1997), Griffin and Karolyi (1998), Chan, Covrig, and Ng (2005), Eun, Huang, and Lai (2008), and Christoffersen et al. (2012).

[2] These statistics and an exposition of the role of the stock markets in China are provided in "China embraces the markets", *The Economist*, July 11, 2015.

1994; Bekaert et al., 2011).[3] Third, during global downturns investors rush out of equity markets of emerging countries, leading to the markets' often precipitous declines (Gelos and Wei, 2005; Jotikasthira, Lundblad, and Ramadolrai, 2012). Fourth, direct trading in foreign securities is hindered by costs and investment barriers, including cultural and language hurdles (French and Poterba, 1991; Grinblatt and Keloharju, 2001; Edison and Warnock, 2008). Finally, many institutions face investment policy constraints on direct holdings of emerging market securities.

To implement our diversification method, we use the UN Comtrade database to obtain information on exports from a particular industry of each developed country to a given emerging country included in our dataset. Our dataset includes seven developed and twenty emerging countries over the 1991-2012 period.[4] For each developed country, we use its publicly traded firms to create industry portfolios. We then use data on exports from these industries to emerging countries to infer portfolio weights that result in an index which accesses a single emerging economy ("EE") and has negligible exposure to others. Note that this EE index is composed of industry portfolios from the seven developed markets only and does not contain emerging market equities. Naturally, industries and countries with closer ties to a given emerging economy, as evidenced by higher exports to it, have higher weights in its EE index.

The intuition behind our methodology can be demonstrated with the following example that assumes two industries in a single developed market. Suppose that the first industry exports to just two emerging countries: \$1 of goods to Argentina and \$5 to Poland. The second industry exports \$5 and \$1 to these two countries. A portfolio that buys one unit of the first industry and shorts 1/5 of a unit of the second industry is exposed to just one emerging economy, Poland. Similarly, a portfolio that is long 1 unit of the second industry and short 1/5 of a unit of the first industry accesses only the Argentine economy.

[3]See also Bradshaw, Bushee, and Miller (2004) who show that firms with high level of conformity to accounting standards have greater institutional ownership; Gelos and Wei (2005) and Aggarwal, Klapper, and Wysocki (2005) who document that both country- and firm-level transparency in disclosure and policy influence mutual funds' allocations; and Doidge, Karolyi, and Stulz (2007) who demonstrate that country characteristics explain variations in corporate governance and transparency.

[4]We use export data at the industry level because exports at the firm level are not available. Compustat segment files are insufficient as they provide firm-level foreign sales only for U.S.-listed firms and, more importantly, only for broad geographic regions such as Europe rather than for specific countries. While imports may also be interesting to consider, the data available to us are limited to exports only.

Our empirical findings can be summarized as follows. First, we show that developed markets, by providing deeper access to emerging economies, still offer substantial diversification benefits. We confirm the important finding of Christoffersen et al. (2012) that correlations within developed market equity indices have increased markedly. However, correlations between our EE indices have remained stable and low throughout the sample, suggesting that it is early to conclude that diversification gains available through developed market investments have significantly declined. We also observe that while the cross-correlation of developed and emerging market equity indices has been increasing throughout the sample, the cross-correlation of developed market and EE indices has not, which suggests the growing relative value of economic diversification.

Second, we show that the EE portfolios deliver substantial performance benefits relative to equity indices of either developed or emerging markets. While the EE portfolios generate average returns that are approximately equal to those of developed and emerging market indices, they do so with substantially lower volatility. The differences in volatility are due to the fact that the EE portfolios contain firms from seven developed countries and hence are more diversified than a single emerging or developed market. As a result, the average Sharpe ratio of the EE indices (0.34) is significantly higher than those of the equity indices of either emerging or developed markets (0.21 for both).

The benefits are also apparent when examining factor-adjusted performance. When using the four global factors of Fama and French (2012) and even after adding the excess return of the corresponding emerging market equity MSCI index as a fifth factor, 17 of 20 EE portfolios generate positive alphas. The average alpha is substantial, between 3% and 7% annually, depending on the factor model used. We show that this result is not explained by exposure to foreign currencies. The high alphas may be a consequence of mispricing (c.f., Huang, 2014); they could also reflect compensation for foreign sales risk, consistent with the arguments of Amihud, Bartov, and Wang (2015). If the latter is the case, then factors based on EE indices may prove valuable in measuring risk-adjusted performance of international investments.

Our third result sheds light on the sources of the diversification gains. We show that benefits from diversifying via EE portfolios are particularly strong during recessionary periods. During such times, an investment based on the EE portfolios outperforms the one based on emerging market equity indices by 17% annually with a substantially lower volatility. These results are consistent with the findings of Gelos and Wei (2005) and Jotikasthira, Lundblad, and Ramadolrai (2012) who show that investors avoid low-transparency emerging markets during global downturns. While developed market firms that export to emerging countries can also suffer during such times, they are not subjected to the same magnitude of sales as are public emerging market firms (see Estrada, 2002; Boyer, Kumagai, and Yuan, 2006; Gelos, 2011). Our results thus suggest that investors exposed to emerging economies through equities in developed markets are better hedged against global market downturns when the diversification benefits are most valuable.

Fourth, we perform mean-variance spanning tests to analyze the EE portfolios (see Huberman and Kandel, 1987; Bekaert and Urias, 1996; Errunza, Hogan, and Hung, 1999). The results of both GMM and likelihood ratio tests suggest that while emerging market equity indices offer incremental gains to an investor holding a portfolio of developed markets indices, they offer limited benefits to an investor also holding EE portfolios. To evaluate the *economic* significance of the tests, we perform the mean-variance step-down analysis suggested by Kan and Zhou (2012). We find that our EE portfolios shift the efficient frontier by an economically large magnitude, whereas emerging market equity MSCI indices do not. We draw a similar conclusion when estimating changes in the Sharpe ratios of tangency portfolios. These findings confirm and quantify the value of diversifying via the EE portfolios.

Fifth and finally, we quantify time-varying *expected* diversification benefits by proposing a model that builds on the intuition in DeSantis and Gerard (1997). Our model shows that the average expected gains from adding the EE portfolios to the benchmark developed markets indices reach 2.9% annually.

Given the benefits of economic diversification that we document, it is prudent to emphasize the empirical feasibility of our diversification approach. While we restrict weights of any industry to be between -1 and 1 so as to avoid highly levered positions in the EE indices, actual short-selling involved is limited. Only 18% of industries are short-sold at any time, and the average portfolio weight of an industry being shorted is just -3.8%. Our results are not meaningfully affected if we disallow shorting. Also, exports are sticky, and consequently the EE portfolios have stable weights over time and low turnover, which is crucial for strategic asset allocation. Our use of lagged export data prevents a look-ahead bias, and we further verify robustness to using exports lagged an additional year and to using expected exports. We show that our results are also robust to using different industry classifications and to modifying EE portfolio construction methods.

Our work relates to the research on international diversification through multinational corporations. In an influential paper, Errunza, Hogan, and Hung (1999) take the point of view of a U.S. investor and use regression-fitted returns to mimic equity indices of emerging countries with 30 multinationals and other foreign investment vehicles. A crucial point of distinction of our paper is that our goal is not to mimic *equity indices* but to obtain exposure to the emerging countries' *overall economies.* We show that our EE portfolios indeed provide access to emerging economies and offer benefits above those available by investing in emerging market equity indices.[5] Our method of accessing foreign economies via export-oriented industries of developed markets is novel and exploits the closeness of economic, cultural, and historical ties between countries.

Qian (1996), Riahi-Belkaoui (1998) and Cai and Warnock (2012) show that U.S. investors can obtain foreign exposure by holding domestic equities with sales abroad. Data limitations prevent these studies from assessing the gains from exposure to a particular emerging country. Multinationals almost never break down their sales by individual countries but report them for a broad region such as Europe. Inferring how much sales were made specifically to, say, Hungary is thus impossible without strong assumptions. By contrast, we can create a portfolio targeting *any* foreign economy, which allows us to study diversification benefits of accessing emerging economies via developed markets. Our approach also takes a broader point of view

[5]The goal of the methodology in Errunza, Hogan, and Hung (1999) is to mimic emerging market equity indices, and doing so perfectly would produce the indices themselves. Hence comparing the diversification benefits offered by our EE indices relative to those offered by the emerging market MSCI equity indices is a suitable one.

as it applies to investors in multiple developed markets. Our method is flexible in that it can be easily modified to examine potential benefits for an investor in any country wishing to diversify into any other country indirectly via multinationals. When we perform our analysis from the point of view of investors in different developed countries, we find that diversifying via EE indices is particularly beneficial for non-U.S. investors.

I. Accessing Emerging Economies via Developed Markets

In this section, we describe the data and the methodology to access emerging economies by investing in publicly traded firms of export-oriented industries in developed countries. We also provide evidence that our approach is successful in accessing emerging economies.

A. Data

We obtain the data from several sources. First, UN Comtrade provides exports at the industry level for country pairs. Boutchkova et al. (2012) convert these data, which are categorized according to the Standard International Trade Classification, into two-digit SIC codes. We obtain the converted data for the 1991-2011 period from the authors for seven developed countries: Australia, Canada, France, Germany, Japan, United Kingdom, and United States.[6] These countries are geographically dispersed and have historical, cultural, and economic ties to a wide range of emerging countries, making them particularly suitable for our purposes. All export numbers are converted into U.S. dollars.

Second, we collect market capitalizations, U.S.-dollar returns, and SIC classifications for all publicly traded developed market firms from Datastream. We then construct value-weighted portfolios for each two-digit SIC code and each developed country in our sample.[7] These industry portfolios serve as components to create emerging economy indices. We form the EE portfolios to access 20 emerging economies: Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru,

[6] We thank Hitesh Doshi for providing the data. We refer the readers to Boutchkova et al. (2012) for details. While imports may also be interesting to consider, the data available to us are limited to exports only.

[7] In Appendix A, we confirm that our findings are robust to re-defining the industry set from two-digit SIC codes to 17 industries classified on Ken French's data library.

Philippines, Poland, South Korea, Thailand and Turkey. Our choice of this set of countries is driven by (i) them being classified as emerging by MSCI as of the beginning of our sample period, and (ii) the availability of data on these countries to conduct the required tests.

We also collect from Datastream U.S.-dollar returns on MSCI equity market indices for both developed and emerging countries. We obtain the indices not only for the seven developed countries for which we have export data but also for nine other countries to allow for direct comparison of our correlation analysis results with those in Christoffersen et al. (2012). These countries are Austria, Belgium, Denmark, Hong Kong, Ireland, Italy, Netherlands, Singapore, and Switzerland. Finally, we obtain global factors from Ken French's data library. We use lagged export data for portfolio construction, and consequently our returns sample covers the period from 1992 to 2012.

B. Methodology

Our goal is to create an "EE" index that captures exposure to a target emerging economy but contains only investments available in developed markets. In creating this index, we want to minimize exposure to other non-target emerging countries. For example, to access the Moroccan economy from the French market, we need to create a portfolio of publicly traded French securities. To be successful at accessing solely the Moroccan economy, this portfolio must achieve two outcomes. First, it must have as low as possible of an exposure to the remaining emerging economies. Second, its exports to Morocco must be economically large.

We create the EE index for a target emerging economy n from the perspective of one developed market $k \in \{1, ..., K\}$ as follows. Denote the emerging countries by $i \in \{1, ..., N\}$ and the industries in the developed market k by $j \in \{1, ..., J\}$. Define X^k as the $J \times N$ matrix containing U.S. dollar exports of each industry j in country k to each emerging country i. As we just described, our objective is to find the $1 \times J$ weight vector $w^{k,n}$ that gives the maximum exports-based exposure to the desired emerging economy n while keeping exposure to the remaining emerging countries at a minimum. Mathematically, this goal can be achieved with a variety of objective functions and constraints. For example, optimization can be done for each pair of developed and emerging countries or jointly for all pairs; the objective function may be set to maximize exposure to the target country n subject to minimizing exposure to the others, or vice versa; and different boundaries may be imposed on weights. We achieve our objective by solving the optimization problem:[8]

$$\min_{w^{k,n}} \sum_{i=1, i \neq n}^{N} \left[\left(w^{k,n} X^{k} \right)_i \right]^2$$

such that

$$\begin{aligned} -1 \ \leq \ \left(w^{k,n} \right)_j \ &\leq \ 1, \quad \forall\, j \in \{1, ..., J\} \\ \sum_{j=1}^{J} \left(w^{k,n} \right)_j \ &= \ 1, \text{ and} \\ \left(w^{k,n} X^{k} \right)_n \ &\geq \ \frac{1}{J} \left(\not\Vdash^{1 \times J} X^{k} \right)_n, \end{aligned}$$

where $(V)_i$ is the ith element of the row vector V, and $\not\Vdash^{1\times J}$ is the $1 \times J$ vector of ones.

We thus set minimizing the sum of squared exports to non-target emerging economies as our objective. The first constraint avoids extremely large leveraged positions to any industry j. In Appendix A, we show that short-selling required to construct the EE portfolios is minimal and that our results are robust when restricting the weights to be non-negative. The second constraint guarantees that the EE portfolio weights sum to one. The last condition ensures that exports to the target country are economically large. Specifically, it avoids assigning large weights to industries with trivial dollar exports to the target economy.

To construct the EE index for a particular emerging economy n (e.g., Morocco), we solve the above problem at the end of every year t seven times: once for each developed country k. Using the resultant weights, we compute buy-and-hold returns in year $t + 1$ from the perspective of each developed country (e.g., U.S.-Morocco, France-Morocco, etc.). In other words, we create seven return indices for each of the 20 emerging economies (all possible k-n combinations). We compute an overall EE index for emerging country n by taking the weighted average of the seven k-n indices. To avoid a look-ahead bias, the weights are determined by the proportion of exports of the developed country k to the emerging country n relative to

[8]In Appendix A, we show that our results are robust to modifications of the methodology. We do not expect our results to be meaningfully affected by other reasonable permutations of the optimization problem.

the total exports of all seven developed countries to the emerging country n in the year prior to the optimization year. Exports are sticky, and consequently our EE portfolios have stable weights over time and low turnover, on average 60% per year. The stability of trade networks also suggests that using weights from expected exports, forecasted using an autoregressive model, does not meaningfully impact our results, as we confirm in Appendix A.

Table I summarizes average proportions of exports of each developed country to each emerging country in our sample. For example, 55.1% of total exports from the seven developed countries to Argentina come from the U.S. In fact, the U.S. is the largest exporter to all of the Latin American countries. Therefore, the EE index for these countries will have higher weight on the United States. In case of the four European emerging countries in our sample, Germany is the largest exporter. For all the Asian countries except India, Japan is the largest exporter. For Morocco, France is the largest exporter, consistent with the historical relations between the two countries. The export weights of each developed country to a given emerging country are intuitive and highlight economic, cultural, and historical ties between countries. These ties implicit in trade flows is precisely what we exploit to obtain exposure to emerging economies by investing solely in developed market firms.

C. Do EE Indices Provide Access to Emerging Economies?

In creating the EE indices, our goal is to obtain exposure to the overall economy of a target emerging country. While exploiting trade networks as we do in forming the EE indices can be expected to help achieve this objective, we now use several tests to verify the extent to which we are able to access the emerging economies.

We begin by computing the average correlation of returns of the EE portfolios and the corresponding emerging market MSCI indices. A high correlation would indicate a failure in achieving our objective of accessing the overall economy rather than the publicly traded equity market. We find that the average correlation, 0.4, is not excessive, providing first indication that our EE portfolios capture exposure to the non-equity-markets side of emerging countries.

If our portfolios capture the underlying economy rather than just the public equity index, we would expect the correlation between our portfolios and the MSCI indices to increase with the size of the equity markets relative to the overall economy. Two pieces of evidence support this hypothesis. First, we find that the correlation between the developed market MSCI indices and the "developed economy" indices constructed using our methodology is 0.7, almost double the corresponding correlation between the emerging market MSCI and EE indices.[9]

Second, we consider two proxies for the size of a country's public markets relative to the size of its overall economy. From Datastream, we collect sales and market capitalizations, in U.S. dollars, for all publicly listed firms in the countries in our sample (both emerging and developed). From World Bank, we obtain nominal GDP data, also in U.S. dollars. We find that both of our proxies, the sales-to-GDP ratio and the market capitalization-to-GDP ratio, relate strongly to the correlation of the economy indices we create and the MSCI indices.[10] That is, as the size of the equity markets relative to the overall economy increases, the correlation between our portfolios and the MSCI indices also increase. For example, for France (U.K.) the correlation of returns of the "developed economy" index and the corresponding MSCI equity index is 0.78 (0.79), and the average ratio of public company sales to GDP is 0.99 (1.09). By contrast, the correlation of returns of the EE index of China (Morocco) and the MSCI index is 0.32 (0.33), and the average sales-to-GDP ratio is 0.24 (0.25).

II. Empirical Results

In this section, we first show that EE indices offer distinctive correlation benefits, surpassing those available by investing in developed market MSCI indices. Second, we find that EE portfolios generate average returns comparable to those offered by emerging market MSCI indices but with considerably lower volatility. Consequently, Sharpe ratios of the EE portfolios exceed those of *both* developed and emerging market MSCI indices. Third, we use mean-variance

[9]To create the developed economy index for a particular country, we use the six other developed markets in our sample and otherwise follow the same methodology as when creating the EE indices. To be clear, our objective is to access emerging economies via developed markets, not to access developed economies via developed markets. However, looking at the latter in this section of the paper is informative to gauge the ability of our methodology to access economic activity of countries.

[10]Admittedly, the two proxies we use are imperfect. For example, the market capitalization is the present value of future cash flows, but the GDP is a measure of aggregate production in a given period. That we find support for our conjecture even with these noisy proxies suggests that EE indices do access the overall economies rather than the public equity indices.

spanning and Sharpe ratio tests to confirm that the EE portfolios yield significant diversification benefits to a developed market investor. Overall, our new route to accessing emerging economies via developed markets offers large performance and diversification benefits.

A. Correlations

To evaluate the relative performance of the EE indices in achieving diversification benefits, we begin by studying the level and dynamics of correlations of EE and MSCI indices. We compute correlations using the dynamic conditional correlation (DCC) model (Engle, 2002).[11] Panel A of Figure 2 presents average bilateral correlations of returns of all EE indices, all emerging market MSCI indices and all developed market MSCI indices. We compute bilateral correlations for each pair within each of these three groups of indices and average across all pairs to derive the correlation for each group.

Consistent with results of Christoffersen et al. (2012), average correlations within both developed market and emerging market MSCI indices exhibit a significant upward trend. This evidence has been interpreted as indicating that diversification benefits within both developed and emerging markets have been declining. For our EE indices, the average correlation is lower than the correlation within the MSCI developed markets; the only exception is the 1999-2003 period, when average correlations within these two sets of indices are similar. Importantly, during the second half of the sample, when correlations within developed markets MSCI indices have been particularly high and increasing, correlations within EE indices have been moderate and stable. In other words, during the period when diversification benefits available via developed market MSCI indices have been disappearing, our approach has offered the promise of diversification gains.

We next take a point of view of investors in developed markets and compare the diversification benefits provided to these investors by the EE indices and the emerging markets MSCI indices. We plot in Panel B of Figure 2 average cross-correlations of developed market MSCI indices with either our EE indices or emerging market MSCI indices. The level and

[11] Appendix B contains the details of model specification. DCC computations do not allow for missing data, and hence the sample of correlations spans the period from 1996 to 2012.

dynamics of the two time-series of correlations are similar, suggesting that it is possible to achieve international diversification by accessing emerging economies uniquely via developed markets' export-oriented industries. We also observe that while the cross-correlation of developed and emerging market MSCI indices has been increasing throughout the sample, the cross-correlation of developed and EE indices has not exhibited a trend in the second half of the sample. This result suggests the growing *relative* value of indirect diversification.

In Figure 3, we explore in more detail the ability of the EE indices to provide diversification benefits by considering the perspective of investors from each developed country separately. Average cross-correlations of the MSCI index of each developed country with either the EE portfolios or the emerging market MSCI indices exhibit patterns similar to those we just observed in the bottom panel of Figure 2. The results suggest that the EE indices offer diversification benefits to investors of *each* considered developed market.

Figures 2 and 3 paint an informative picture of the level and dynamics of average correlations and highlight potential diversification benefits offered by the EE indices. Yet, the picture may be incomplete because taking means may omit useful information about the cross-section of correlations. Figure 4 provides additional perspective by showing the distribution of correlations. The entire distribution of correlations within developed and emerging market MSCI indices and cross-correlations of these two sets of indices has been steadily increasing during the sample period (Panels A, B, and D). By contrast, the corresponding increases for EE indices have been largely absent since the late 1990s.

We next study whether EE portfolios offer different diversification benefits in down and up markets by studying threshold correlations.[12] We standardize returns of all indices by their respective unconditional means and GARCH(1,1) standard deviations. For each pair of countries, the threshold correlations are given by computing correlations of the two countries' returns when both are below (from 0 to 0.5) or above (from 0.5 to 1) the specified percentile levels shown on the x-axis in Figure 5. We plot the average threshold correlations separately for developed market MSCI indices, emerging market MSCI indices, and EE portfolios. The

[12] Studies analyzing diversification benefits conditional on market states include Lin, Engle, and Ito (1994), DeSantis and Gerard (1997), Longin and Solnik (2001), Ang and Bekaert (2002), and Ang and Chen (2002).

figure shows that both the downside and upside threshold correlations of the EE indices are much lower than those of developed market MSCI indices. In Figure 6, we observe the same patterns when analyzing each of the developed markets individually.[13]

Overall, our results suggest that accessing emerging economies via investments in developed markets delivers correlation and tail dependence benefits similar to those of emerging market equity indices while offering the depth and transparency of developed markets.

B. Moments of returns of MSCI and EE indices

We now evaluate the returns of the EE indices. Our methodology aims to access the underlying economies of emerging countries, and hence the performance of the EE indices should be tied closer to the performance of the emerging economies rather than to that of the emerging market public equity indices. Nonetheless, equity indices are readily available and present a natural point of comparison. In Figure 7 we plot cumulative returns and in Table II and Figure 8 we summarize the moments of returns for EE and equity indices for different countries. Three observations are noteworthy.

First, average excess returns of the EE and MSCI indices are similar for every emerging market. While emerging market MSCI indices generate an average return of 6.9% per year (second bar in Panel A of Figure 8), the magnitude for the EE indices is slightly lower at around 5.3%. The average returns of both sets of indices are higher than the corresponding value of 4.5% for all developed market MSCI indices shown in the first bar of Figure 8.

Second, the volatility of returns of EE indices is substantially lower than that of emerging market MSCI indices. This holds for each of the 20 countries we consider. The average volatility across the emerging markets is 17% for the EE indices and double that, 34%, for MSCI indices (Panel B of Figure 8). This is not surprising because developed markets are known to have lower unconditional volatility, and the EE portfolios are constructed from developed market firms. The EE portfolios also exhibit lower volatility than does the average developed country MSCI index (23%). This difference is due to EE portfolios containing firms from all seven

[13] We report results for 16 developed markets for comparability with Christoffersen et al. (2012). Our correlation results for the developed market MSCI equity indices are very similar to theirs.

developed markets and hence being more diversified than a single developed market.

Third, Sharpe ratios of the EE indices are on average significantly higher than those of the MSCI indices of either developed or emerging markets. This is the direct consequence of returns being on average similar across the three sets of indices but much less volatile for the EE portfolios. On average across all emerging countries, the Sharpe ratio for the EE indices is 0.34 compared to 0.21 for both sets of MSCI indices.

An interesting question from the perspective of investors in developed markets, is whether adding emerging country indices to their set of benchmark assets delivers incremental benefits. To quantify the benefits, we assume that investors' benchmark portfolios are the equally-weighted MSCI indices of the developed countries.[14] We then evaluate changes in portfolio performance after adding either the emerging market MSCI indices or the EE indices. We summarize the results of this analysis in Table III.

Panel A of Table III shows that an investor with the 1/N allocation to developed market MSCI indices would have generated an average excess return of 4.5% with volatility of 17.9% per year. The 1/N investment in emerging market MSCI indices would have delivered a higher return with slightly higher volatility, improving the Sharpe ratio from 0.25 to 0.36. Strikingly, the 1/N allocation to the EE indices would have delivered an even higher Sharpe ratio of 0.51, driven by the low volatility of the portfolio of just 10.4%. The last two columns of Table III show that an investor in developed markets who adds emerging market MSCI indices to the portfolio would have generated an average return of 5.7% with volatility of 17.6%, improving the Sharpe ratio from 0.25 to 0.32. Adding the EE indices instead results in an even more dramatic improvement in the Sharpe ratio, to 0.38, driven by a large reduction in volatility.

When should we expect greater incremental benefits from investing in the EE portfolios rather than the emerging market MSCI indices? To answer this question, we split the sample into two sub-periods: U.S. recessionary and expansionary periods as identified by the NBER. While our analysis is based on multiple developed markets rather than the U.S. alone, reces-

[14] We use the equally-weighed rule as a benchmark for two reasons. First, DeMiguel, Garlappi, and Uppal (2007) show the out-of-sample outperformance of the 1/N policy. Second, the equally-weighted strategy is easy to implement since it does not rely either on estimation of the moments of asset returns or on optimization. In Section II.D.3, we use optimal weights obtained from mean-variance optimization instead of equal weights; our results remain robust.

sions in the U.S. coincide with slowdowns in the economies around the globe, and so dividing the sample on the basis of the NBER data is suitable for our purposes.

The results, reported in Panels B and C of Table III, suggest that the substantially better risk-return trade-off of the EE indices is due to their relatively stronger performance during recessions. An investor in the EE indices would have outperformed an investor holding either developed or emerging market MSCI indices by 30% per year during recessions and would have generated this performance with considerably lower volatility. A developed market investor who added EE indices to the portfolio would have performed by over 17% per year better relative to an investor adding emerging market MSCI indices. During expansions, the Sharpe ratios of these two investors are similar.

The superior performance of the EE portfolios is consistent with findings of Gelos and Wei (2005) and Jotikasthira, Lundblad, and Ramadolrai (2012) who show that investors avoid low-transparency emerging markets during global downturns. The developed market firms that export to emerging economies also suffer during such times, but not to the same extent as do the public emerging market firms (see Estrada, 2002; Boyer, Kumagai, and Yuan, 2006; Gelos, 2011). As a result, investors exposed to emerging economies through equities in developed markets are better protected against global market downturns when diversification benefits are particularly valuable.

To summarize, our method of accessing emerging economies via export-oriented industries of developed markets generates emerging market average returns but with developed market volatility, and performs particularly well during recessionary periods.

C. Factor-adjusted performance of EE indices

The strong performance of the EE portfolios can plausibly be driven by exposure to either known factors or risks specific to equity markets of developed or target emerging countries. To investigate this possibility, we now examine factor-adjusted performance of the EE portfolios.

Specifically, we run two regressions for each EE index:

$$\text{Model 1:} \qquad R_{i,t} = \alpha_i + \sum_{d=1}^{7} \beta_d R_{d,t}^{\text{MSCI}} + \beta_i R_{i,t}^{\text{MSCI}} + \epsilon_{i,t}, \text{ and}$$

$$\text{Model 2:} \qquad R_{i,t} = \alpha_i + \sum_{f=1}^{4} \beta_f R_{f,t} + \beta_i R_{i,t}^{\text{MSCI}} + \epsilon_{i,t},$$

where $R_{i,t}$ is the excess return of the EE portfolio of emerging country i in month t, $R_{d,t}^{\text{MSCI}}$ is the excess return of the MSCI index of developed market d, $R_{i,t}^{\text{MSCI}}$ is the excess return of the MSCI index of emerging market i, and $R_{f,t}$ are the global market, size, value, and momentum factors from the Ken French's data library.

In both models, we thus include as a factor the return on the MSCI index of the targeted emerging country, $R_{i,t}^{\text{MSCI}}$, to adjust for the component of return that is due to risks specific to the equity market of this country. The first model also adds returns of the seven developed markets whose industries we use to create the EE index. Loadings on these portfolios control for risks specific to the developed countries. In the second model, we instead include the widely considered four factors of Fama and French (2012).

Table IV summarizes alphas from the two models for each emerging country. The results corroborate the earlier evidence that EE indices deliver superior performance. Out of 40 possible country- and model-specific alphas, only three are negative, and all three are statistically indistinguishable from zero. The average alphas across the 20 countries are positive and statistically and economically significant, at 7.2% and 3.2% annually for the two models.[15]

We next investigate whether our results may be due to exposure to foreign currencies. For example, we are interested in whether the high alpha of the Indian EE index is driven by the appreciation or depreciation of the rupee relative to the currencies of the seven developed markets in our sample. To address this question, for each emerging country we compute the real effective exchange rate, which is the trade-weighted exchange rate index designed to measure relative strength of a currency relative to a basket of other currencies adjusted for inflation differentials. We obtain monthly currency series from the Bank of International

[15]In untabulated results, we augment each model by adding conditioning variables to account for the fact that unconditional performance metrics may be unreliable if risk premiums or betas are time-varying (Ferson and Schadt, 1996). The results are similar to those reported here, and we omit them for brevity.

Settlements. For each emerging country, we split the sample into two on the basis of whether its real effective exchange rate growth rate is above or below the in-sample median level. In untabulated results, we find that alphas computed in each sub-sample are nearly identical to the full-sample alphas in Table IV, which suggests that differences in currency exposure are unlikely to be responsible for our results.

What drives high alphas of EE indices? They could be a consequence of mispricing (c.f., Huang, 2014), and could also reflect compensation for risk not captured by the common factors. Consistent with the latter interpretation, Amihud, Bartov, and Wang (2015) argue that foreign sales risk is positively priced in the cross-section of U.S. equities. If this risk-based explanation is responsible for the high alphas, then factors based on the EE indices may prove valuable in measuring factor-adjusted performance of international investments.

D. Mean-variance spanning and Sharpe ratio tests

In this section, we study whether an investor holding developed market equities can benefit from diversifying into emerging country indices. The results of mean-variance spanning, certainty equivalent, and Sharpe ratio tests suggest that EE indices offer economically and statistically superior diversification benefits relative to emerging market MSCI indices.

D.1. Mean-variance spanning tests

We first ask whether individual emerging market MSCI indices (test assets) can be spanned by a set of benchmark assets constructed from developed market equities. If a test asset is not mean-variance spanned by the benchmark assets, an investor can expand the efficient frontier by adding the asset to the portfolio and hence benefit from diversification. For the MSCI index of each emerging market i, we consider two sets of benchmark assets: (i) the seven developed market MSCI indices, and (ii) seven assets chosen from the seven developed market

MSCI indices and the EE index of country i.[16] The mean-variance test involves estimating

$$r_{i,t}^{\mathrm{MSCI}} = \alpha_i + \sum_{b=1}^{7} \beta_{i,b} r_{b,t} + \epsilon_{i,t},$$

where $r_{i,t}^{\mathrm{MSCI}}$ is the return on the MSCI index of emerging country i in month t and $r_{b,t}$ is the return on the benchmark asset b.

Huberman and Kandel (1987) show that $r_{i,t}^{\mathrm{MSCI}}$ is mean-variance spanned by the seven benchmark assets if and only if the following two conditions of our null hypothesis hold:

$$H_0\colon\ \alpha_i = 0;\ \sum_{b=1}^{7} \beta_{i,b} = 1.$$

The hypothesis can be viewed as a test of whether the tangency portfolio has zero weight in the emerging country index. Huberman and Kandel (1987) provide a regression-based likelihood ratio test under the normality assumption. Dumas and Solnik (1995) and Bekaert and Urias (1996) provide generalized method of moments (GMM) based tests of spanning under the stochastic discount factor framework. We use the GMM spanning test under the regression approach since it is superior to the GMM test under the stochastic discount factor approach when $\epsilon_{i,t}$ exhibits conditional heteroscedasticity (see Kan and Zhou, 2012).

Table V reports p-values from the likelihood ratio and the GMM tests. Higher p-values indicate that it is harder to reject the null hypothesis that the test asset is mean-variance spanned by the benchmark assets. Therefore, higher p-values give us greater conviction that adding the emerging market MSCI index does not provide diversification benefits to an investor holding the developed market portfolios.

We reject the null hypothesis in 9 (8) out of 20 emerging countries under the likelihood ratio (GMM) test using the MSCI indices of the seven developed markets as benchmark assets. In other words, MSCI indices of approximately half of the emerging countries provide diversification benefits to an individual investing in the seven developed market MSCI indices. The number of rejected countries declines to just 4 (3) when we include the EE index in the set of

[16] Fixing the number of benchmark assets in these two sets to be equal follows Errunza, Hogan, and Hung (1999) and maximizes the probability of not rejecting the mean-variance spanning test. Doing so is also important because the power of the test critically depends on the number of benchmark assets (e.g., Bekaert and Urias, 1996).

benchmark assets. Thus, once the EE index is added to the portfolio, the emerging market MSCI index offers limited additional diversification opportunity. This evidence complements the findings in Errunza, Hogan, and Hung (1999).

Importantly, including the EE index as a benchmark asset substantially increases p-values for almost all countries. For example, the average p-value across all 20 emerging markets with the seven developed market MSCI indices as benchmark assets is 14% (17%) for the likelihood ratio (GMM) test. The average p-value increases to 42% (44%) when including the EE index as a benchmark asset. This result further highlights the value of EE indices in providing diversification benefits without requiring direct investments into emerging market equities.

D.2. Mean-variance step-down spanning tests

In the previous section, we have examined whether the MSCI index of an emerging market is mean-variance spanned by a set of benchmark assets constructed from developed market equities. In this section, we are interested in the economic rather than statistical significance of the alternative hypothesis.

Kan and Zhou (2012) show that statistical significance, as evidence by a low p-value, does not always imply that the difference between two efficient frontiers is economically large. Why is that? Recall that the mean-variance spanning test is a joint test of $\alpha_i = 0$ and $\sum_{b=1}^{7} \beta_{i,b} = 1$. Since estimating $\delta_i \equiv 1 - \sum_{b=1}^{7} \beta_{i,b}$ does not involve estimating the mean, δ_i can be determined much more accurately than α_i. Therefore, tests of spanning inevitably place a heavy weight on an estimated δ_i than on an estimated α_i. Although this practice is natural from a statistical point of view, it does not take into account the economic significance of the departure from the spanning hypothesis.

Kan and Zhou (2012) offer a geometric interpretation of the two tests. The "first test" on α_i is about the distance between two tangency portfolios. The "second test" on δ_i is about the distance between two global minimum-variance portfolios. A small difference between the global minimum-variance portfolios, while statistically significant, is not necessarily economically important. Also, a big difference in the tangency portfolios can be of great economic importance, but this importance is difficult to detect statistically. Kan and Zhou (2012) design sequential step-down tests to separate the two joint hypotheses. The first test is $\alpha_i = 0$, and the second test is $\delta_i = 0$ conditional on $\alpha_i = 0$.

Table VI reports the results of the two tests. In the left set of columns, our test asset is the MSCI index of a particular emerging country. In the right set of columns, it is the EE index of that country. Our benchmark assets are the MSCI indices of the seven developed markets. We show the p-values from both the commonly used mean-variance spanning test from Table V as well as p-values and sample statistics from the step-down sequential tests.

The results of the first test ($\alpha_i = 0$) show that none of emerging market MSCI indices are able to push the tangency portfolio up to the left by an economically meaningful magnitude. For countries with a rejection on the total (joint) test, the statistical significance is coming from the second test ($\delta_i = 0$). By contrast, 15 of 20 EE indices have rejection for the first step-down test and all 20 indices for the second step-down test. This result strongly suggests that our EE indices are able to expand the efficient frontier of the developed market MSCI portfolios by magnitudes that are not only statistically significant but also economically meaningful.

D.3. Certainty-equivalent rates

To further quantify the economic gains from holding our EE indices, we measure incremental changes in certainty equivalent rates for a risk-averse decision maker. The certainty-equivalent rates can be interpreted as the magnitude of the risk-free return that an investor would be willing to give up in exchange for having our EE indices in the benchmark portfolio. Based on the exponential utility function, certainty-equivalent rates can be computed as:[17]

$$\Delta CEQ \quad = \quad \left(\mu_{DM+EE} - \frac{\gamma}{2}\sigma^2_{DM+EE}\right) - \left(\mu_{DM} - \frac{\gamma}{2}\sigma^2_{DM}\right),$$

where μ_{DM} and σ^2_{DM} are the mean and variance of returns of the optimized portfolio, which consists of the seven developed market MSCI indices, and μ_{DM+EE} and σ^2_{DM+EM} denote the mean and variance of returns of the optimized portfolio constructed after adding the EE index to the set of assets. We consider four levels of the risk aversion coefficients γ: 2, 4, 6 and 8.

[17] See, for example, Avramov (2004), DeMiguel, Garlappi, and Uppal (2007), Ferreira and Santa-Clara (2011), Kan and Zhou (2007), and Tu and Zhou (2004).

Table VII reports the certainty-equivalent rates for each of the emerging economies. On average, investors with risk aversion rates of 2 (8) are willing to forego 2.93% (4.46%) in risk-free annual returns in exchange for having the EE indices in their portfolios. These substantial magnitudes are consistent with the results from the mean-variance step-down tests, reinforcing our arguments that EE indices offer economically large benefits.

D.4. Sharpe ratio tests

We now consider another test to provide further evidence of economic significance of the benefits of diversifying into emerging countries. Specifically, we compute changes in Sharpe ratios associated with the addition of an emerging country index to the benchmark portfolio containing MSCI indices of the seven developed markets. The changes in the Sharpe ratio have a convenient interpretation of the maximum incremental gains that can be achieved by investing in a particular emerging country.

Table VIII shows that increases in Sharpe ratios of the tangency portfolio are substantially larger when adding the EE portfolio than when adding the MSCI index of the corresponding emerging market. Across the 20 emerging countries, the Sharpe ratios increase on average by 0.063 for the EE indices and by just 0.003 for the MSCI indices. Bekaert and Urias (1996) note that formal tests of the statistical significance of changes in Sharpe ratios are challenging because of their unknown distribution. They use Monte Carlo analysis to show that changes of less than 0.057 are not statistically significant. Using this cutoff, changes for none of the 20 countries are significant when adding emerging market MSCI indices. By contrast, 11 of the EE indices deliver statistically significant increases in Sharpe ratios.

E. EE indices constructed from individual developed countries

The closeness of economic, historical, and cultural ties varies significantly across pairs of developed and emerging countries. This variation is what motivates us to use multiple developed markets when creating an EE index for a given emerging country. We now ask how valuable it is to construct the EE portfolios from several developed markets rather than a single one. In other words, how different are the diversification benefits that, for example, French investors can derive using EE indices constructed with just French equities from benefits available to them through EE indices created using all seven developed markets? We address this question using the mean-variance step-down procedure of section II.D.2.

Panel A of Table IX shows that locally constructed EE indices deliver diversification gains relative to the MSCI index of the local developed country. The improvement is the highest for the U.S., consistent with the U.S. firms offering wide sales exposures to emerging countries (see Table I). Panel B shows potential diversification gains that investors in individual developed countries can achieve by also adding EE indices constructed from all seven developed countries. Additional diversification gains are small for U.S. investors since much of the gain is already realized from the locally created EE index. For other countries, the benefits, as measured by alpha from the first test, are economically large, ranging between 0.32% and 0.61% monthly. Taken together, this evidence reiterates the substantial diversification benefits available by investing in EE portfolios. The benefits only increase when we exploit economic ties between countries and construct the EE indices from multiple developed markets.

III. Quantifying the Diversification Benefits

In the mean-variance tests, we assume that investors construct portfolios optimally with the knowledge of the ex-post moments of all assets. In reality, not only do investors not observe the ex-post measures when forming their portfolios, but their perceptions of the levels of risk and expected returns change over time. The important question that arises is how to quantify the *expected* benefits of investing in the EE indices. In this section, we address this question.

A. Full market integration

We assume initially that financial markets are fully integrated and that expected returns are driven by exposure only to the world market portfolio. DeSantis and Gerard (1997) show that expected diversification benefit in this case is driven by the interaction between the time-varying price of market risk and the time-varying quantity of risk (covariance risk). Following their intuition, we propose a model to measure time-varying diversification benefits.

Consider an investor who holds developed market MSCI indices and wants to evaluate the potential benefits of adding exposure to emerging countries. As before, we consider two ways an investor can gain this exposure: through MSCI indices or our EE indices. To be consistent with the exercise in Table III, we use the equally-weighted MSCI indices of the 16 developed markets ("DM index") as the benchmark for the developed market portfolio.

The international asset pricing model suggests that the expected excess return on the DM index should equal $\lambda_{W,t} E_t[cov(R_{DM,t+1}, R_{W,t+1})]$, where $\lambda_{W,t}$ denotes the time-varying price of covariance risk to the market factor, and $R_{DM,t+1}$ and $R_{W,t+1}$ are excess returns of the DM index and the world market portfolio at time $t+1$, respectively. Similarly, the expected excess return on the equally-weighted portfolio of both developed market indices and emerging country – either EE or emerging market MSCI – indices ("DM+EC index") is $\lambda_{W,t} E_t[cov(R_{DM+EC,t+1}, R_{W,t+1})]$, where $R_{DM+EC,t+1}$ denotes the return on the DM+EC index. The levels of risk associated with the two expected returns are $E_t[var(R_{DM,t+1})]$ and $E_t[var(R_{DM+EC,t+1})]$. Therefore, the expected returns of the two investments cannot be compared directly due to different risk exposures.

To measure expected returns at the same level of risk exposure, we calculate the ratio of the conditional variance of the world market portfolio to the conditional variance of the two portfolio returns: $E_t[var(R_{W,t+1})]/E_t[var(R_{DM,t+1})]$ for the DM index, and $E_t[var(R_{W,t+1})]/E_t[var(R_{DM+EC,t+1})]$ for the DM+EC index. By multiplying the expected return and the ratio, we have the expected returns where levels of risk for both assets are normalized to the level of risk for the world market factor. The difference between the two risk-adjusted expected returns is the expected diversification benefit:

$$\begin{aligned}
&E_t[\text{Benefit}_{DM \to DM+EC,t+1}] \\
&= \lambda_{W,t} \times E_t\left[cov(R_{DM+EC,t+1}, R_{W,t+1})\right] \times \frac{E_t[var(R_{W,t+1})]}{E_t[var(R_{DM+EC,t+1})]} \\
&\quad -\lambda_{W,t} \times E_t[cov(R_{DM,t+1}, R_{W,t+1})] \times \frac{E_t[var(R_{W,t+1})]}{E_t[var(R_{DM,t+1})]}.
\end{aligned}$$

The evolution of the diversification benefit can thus be quantified through the interaction of the three terms: (i) time-varying price of the market risk, (ii) time-varying quantity of risk, and (iii) time-varying quantity of the risk normalization factor. To quantify diversification benefits we now estimate these three quantities.

We follow the empirical approach of Dumas and Solnik (1995) to measure the time-varying price of the market risk. We assume that the marginal rate of substitution between nominal returns from time t to $t+1$ has the form

$$M_{t+1} = \frac{1 - \lambda_{0,t} - \lambda_{W,t} R_{W,t+1}}{1 + i_t},$$

where i_t is the conditional risk-free rate and $R_{W,t+1}$ is the nominal return on the world market portfolio from time t to $t+1$. The first order conditions of the portfolio choice problem are:

$$E_t[M_{t+1}(1 + i_t)|\Omega_t] = 1,$$
$$E_t[M_{t+1} R_{j,t+1}|\Omega_t] = 0,$$

where Ω_t is the information set available at time t and $R_{j,t+1}$ is the nominal return of any asset j. Following Dumas and Solnik (1995), we assume that the information set Ω_t is generated by a set of state variables Z_t and that there exists a linear relation between λ_t and Z_t:

$$\lambda_{0,t} = -Z_t \phi_0 \quad \text{and} \quad \lambda_{W,t} = Z_t \phi_W,$$

where ϕ_0 and ϕ_W are constant vectors of weights to state variables. With N assets, we have $1+N$ vector of errors $\epsilon_{t+1} = (u_{t+1}, h_{t+1})$, where u_{t+1} and h_{t+1} are the residual vectors from the first and the second equation of the first order conditions of portfolio choice problem above, respectively:

$$\begin{aligned} u_{t+1} &= 1 - M_{t+1}(1 + i_t), \\ h_{j,t+1} &= (1 - u_{t+1}) R_{j,t+1} \ \forall \ j = 1, ..., N. \end{aligned}$$

Given our assumption on the information set Ω_t, we have $E_t[\epsilon_{t+1}|Z_t] = 0$, which implies the unconditional relation $E[\epsilon_{t+1} Z_t] = 0$. This condition leads to $l \times (1+N)$ sample moment conditions: $Z'\epsilon$, where l is the number of instruments, Z is a $T \times l$ vector of instruments, and ϵ is a $T \times (1+N)$ matrix of residuals.

Using the U.S. dividend yields, term spreads, and default spreads as instrumental variables, we apply the GMM to test assets to estimate the price of world market risk. We use the global market factor and the 25 global portfolios formed on size and book-to-market from Ken French's data library as our world market factor and test assets, respectively. Figure 9 shows the time-varying price of covariance risk. The black line is the estimated $\lambda_{0,t}$ and the red dotted line is the estimated $\lambda_{W,t}$. For comparison, the blue line plots the constant price of world market risk by imposing $Z_t = 1$ for all t. Compared to the constant price of risk of about 3.7% per year, $\lambda_{W,t}$ exhibits significant time variation with a mean of 3.2% and a standard deviation of 1.8%, while $\lambda_{0,t}$ is very close to zero throughout the sample.

Multiplying the estimated time-varying price of market risk with the quantity of risk and the risk normalization factor estimated using the DCC model of Engle (2002), we quantify the expected incremental gains of diversifying into emerging markets using either emerging market MSCI indices or the EE indices. We plot the gains in Panel A of Figure 10. Consistent with the empirical results in section II, we find that investors can enjoy substantial benefits by diversifying using the EE portfolios. The expected gains average 1.7% per year and are particularly strong at the height of the financial crisis. By contrast, investors are actually worse off by adding emerging market MSCI indices: the average "benefit" is negative at -0.9% annually. This result is surprising considering that the average of all bilateral cross-correlations of developed market MSCI indices with emerging market MSCI indices in Figure 2 is slightly lower than that with EE indices. How can this be?

There are two potential explanations. First, the correlation measure does not take into account the time-varying quantity of risk from holding a non-diversified stand-alone asset. Therefore, the expected return can be lower after adjusting the level of risk to the conditional variance of the world market portfolio. In this case, investors are indeed worse off by adding the emerging market MSCI indices since the incremental gains in the expected return are more than offset by the higher conditional variance. Second, our assumption that markets are fully integrated and that the differences in the expected returns are thus driven solely by exposure to the world market portfolio may be violated. In this case, the true conditional expected returns for emerging market MSCI indices may be underestimated in our model relative to those in a model with market segmentation. We now examine the diversification benefits under the assumption of partial market integration.

B. Partial market integration

Building on Bekaert and Harvey (1995), we now assume that there are two factors: the world market factor and the emerging market factor. To remain consistent with the analysis in the previous sections, we use equally-weighted emerging market MSCI indices to proxy for the emerging market portfolio. We orthogonalize the returns on this portfolio, $R_{EM,t+1}$, to the returns on the global Fama-French market factor, $R_{W,t+1}$, by estimating the regression

$$R_{EM,t+1} = \alpha + \beta R_{W,t+1} + \epsilon_{EM,t+1}.$$

We define the world and emerging market factors as $R_{W,t+1}$ and $\epsilon_{EM,t+1}$, respectively, and denote the corresponding prices of risk as $\lambda_{W,t}$ and $\lambda_{EM,t}$.

Under the partial market integration assumption, investors require compensation not only for exposure to the world market factor but also for exposure to the emerging market factor. Therefore, the two-factor model implies that the risk-adjusted expected returns for any asset j should equal $\lambda_{W,t} \times E_t[cov(R_{j,t+1}, R_{W,t+1})] + \lambda_{EM,t} \times E_t[cov(R_{j,t+1}, \epsilon_{EM,t+1})]$. From the perspective of an investor who holds benchmark index j, the expected diversification benefit of using a broader index k is

$$\begin{aligned}
& E_t[\text{Benefit}_{j \to k,t+1}] \\
&= \{\lambda_{W,t} E_t[cov(R_{k,t+1}, R_{W,t+1})] + \lambda_{EM,t} E_t[cov(R_{k,t+1}, \epsilon_{EM,t+1})]\} \frac{E_t[var(R_{W,t+1})]}{E_t[var(R_{k,t+1})]} \\
&\quad - \{\lambda_{W,t} E_t[cov(R_{j,t+1}, R_{W,t+1})] + \lambda_{EM,t} E_t[cov(R_{j,t+1}, \epsilon_{EM,t+1})]\} \frac{E_t[var(R_{W,t+1})]}{E_t[var(R_{j,t+1})]}.
\end{aligned}$$

Panel B of Figure 10 plots the expected benefits to an investor in the developed market MSCI indices of diversifying into emerging countries. Diversifying via emerging market MSCI indices offers on average higher expected gains (0.3% per year) than those estimated under the assumption of full market integration (-0.9%). This is not surprising since the conditional expected returns of the emerging market MSCI index are higher when allowing covariance to the emerging market factor to be priced.[18] The gains are lower in the early part of the sample

[18] The average prices of the world market and the emerging market risk factors are 4.9% and 2.8% annually when allowing for market segmentation.

due to time variation in the price of the emerging market factor. Importantly, even assuming market segmentation, EE portfolios continue to offer expected diversification benefits that are higher (2.9%) than those available through investments in emerging market MSCI indices.

IV. Conclusion

Equity markets capture but a sliver of economic activity of many countries. As a result, assessing the benefits of international diversification using foreign equity market indices can significantly understate potential diversification gains. We propose a new diversification approach to gain exposure to a foreign country's overall economy rather than just its public equity market. We apply this approach to revisit benefits of investing in emerging countries, where, despite rapid economic growth, stock markets have remained small relative to the size of the economies. We show that diversifying into emerging economies by investing solely in publicly-traded export-oriented firms in developed markets provides benefits beyond those available through emerging market equity indices.

Our emerging economy portfolios deliver factor-adjusted returns above 7% annually and generate Sharpe ratios exceeding those of equity indices of both developed and emerging markets. Mean-variance and step-down tests show that the emerging economy portfolios shift the efficient frontier by an economically large magnitude. Dynamic conditional correlation analysis suggests that developed markets, by providing deeper access to emerging economies, *still* offer sizeable diversification benefits. Accessing emerging economies uniquely through developed markets is also attractive because it mitigates numerous challenges and costs of investing directly in emerging markets. We expect the benefits of our economic diversification to be even stronger when targeting smaller "frontier" economies.

Our results suggest that the route to access emerging economies via investments in developed markets delivers the best of both worlds: It generates emerging market average returns but with developed market volatility, and provides correlation benefits similar to those of emerging market equity indices while benefiting from the depth and transparency of developed markets.

Appendix

A. Robustness

In this section, we conduct three tests to evaluate robustness of our findings to the empirical choices we make when obtaining the base-case results reported in the paper. We now describe the three tests and then summarize their results. First, we re-define our industry set from two-digit SIC codes to 17 industries classified on the Ken French's data library.

For our second set of robustness tests, we leave the industry definition intact and instead modify the definition of exports. Although exports are sticky and we already use year t exports to avoid a look-ahead bias when constructing the EE indices for year $t+1$, we now consider an even more conservative approach. Specifically, we forecast year t exports at the country-pair level with an AR(1) model and using only data up to year $t-1$. We thus use the export data lagged by an additional year when creating the EE indices.

Our third modification of the empirical methodology involves changing the restriction we place on portfolio weights when constructing the EE indices. Recall that we require the portfolio weight of the developed market industry j exporting to the emerging country i to be $-1 \leq w_{j,i} \leq 1$. A potential concern with this restriction is that it does not preclude short-selling, which may be challenging to implement in practice. Given this concern, and given the large benefits of economic diversification that we document, it is prudent to emphasize that our approach involves limited short-selling. Panels A and B of Table A.I show, respectively, the average fraction of industries that are short-sold and the average portfolio weights conditional on short-selling from the perspective of each of the developed markets. On average across the EE indices, only 18% of industries are short-sold at any time. Moreover, conditional on shorting, the average portfolio weight of an industry being shorted is just -3.8%. Despite this evidence that short-selling is unlikely to impact our results, for our third robustness test we disallow short-selling: $0 \leq w_{j,i} \leq 1$.

We summarize the results of the robustness tests in Table A.II. To conserve space, we report a subset of the results, but in untabulated analysis we confirm that all of our findings remain robust to the considered changes in the empirical methodology.[19] In Panel A of Table A.II, we report average alphas from the regressions of excess returns of EE indices of each of the 20 emerging countries on the same factors as in Table IV. In Panel B of Table A.II, we summarize the number of rejected countries at the 5 percent significance level, obtained from the mean-variance step-down spanning tests as in Table VI.

The average alphas are all positive and statistically significant. We also find that our EE indices expand the efficient frontier of the developed market MSCI portfolios by an economically large magnitude. Taken together, these findings confirm the robustness of our results to (i) considering alternative industry definitions, (ii) using forecasted exports to further alleviate any concerns about a look-ahead bias, and (iii) requiring no short-selling in construction of the EE portfolios.

B. Dynamic conditional correlation model

In this section we describe the dynamic conditional correlation (DCC) model of Engle (2002). To standardize the individual equity return series, we assume the return and the conditional variance dynamics of equity index i at time t are given by

$$\begin{aligned} r_{i,t} &= \mu_i + \epsilon_{i,t} = \mu_i + \sigma_{i,t} z_{i,t}, \\ \sigma_{i,t}^2 &= \omega_i + \alpha_i \epsilon_{i,t-1}^2 + \beta_i \sigma_{i,t-1}^2, \end{aligned}$$

where μ_i denotes the unconditional mean, $\sigma_{i,t}^2$ the conditional variance, $z_{i,t}$ a standard normal random variable, ω_i the constant term, α_i the sensitivity to the squared innovation, and β_i the sensitivity to the lagged conditional variance. Since the covariance is the product of the correlation and standard deviations, we can write the covariance matrix (Σ_t) of the returns at time t as,

$$\Sigma_t = D_t R_t D_t$$

[19]Interestingly, we find that the Sharpe ratios of the EE indices are actually higher when we disallow short-selling. The reason for this increase is that when we create the EE indices, we want to obtain exposure to a single emerging economy, and permitting negative weights allows us to do it. As a simple illustration, when we create the Morocco EE index, we buy French firms in industry A, which also do business in, say, Indonesia. We then undo this unwanted exposure to Indonesia by selling firms in industry B that do business there. By contrast, when we restrict the weights to be non-negative, we can no longer undo exposure to other emerging economies. The resulting EE index therefore turns out to be more "diversified" and yields even lower volatility.

where D_t has the standard deviations $(\sigma_{i,t})$ on the diagonal and zero elsewhere, and R_t is an $n \times n$ conditional correlation matrix of standardized returns (z_t) at time t. Let Q_t denote the conditional covariance matrix of z_t and R_t^{DCC} the DCC correlation.

$$
\begin{aligned}
Q_t &= (1 - \alpha_Q - \beta_Q)\overline{Q} + \alpha_Q \tilde{Q}_{t-1}^{\frac{1}{2}} z_{t-1} z_{t-1}' \tilde{Q}_{t-1}^{\frac{1}{2}} + \beta_Q Q_{t-1}, \\
R_t^{DCC} &= \tilde{Q}_t^{-\frac{1}{2}} Q_t \tilde{Q}_t^{-\frac{1}{2}},
\end{aligned}
$$

where α_Q is the sensitivity to the covariance innovation of z_t, β_Q is the sensitivity to the lagged conditional covariance of z_t, $\tilde{Q}_t$ replaces the off-diagonal elements of Q_t with zeros but retains its main diagonal, and $\overline{Q}$ is the unconditional covariance matrix of z_t. To estimate our model, we follow the methodology in Engle (2002). We refer the reader to the latter paper for a complete description of the estimation methodology.

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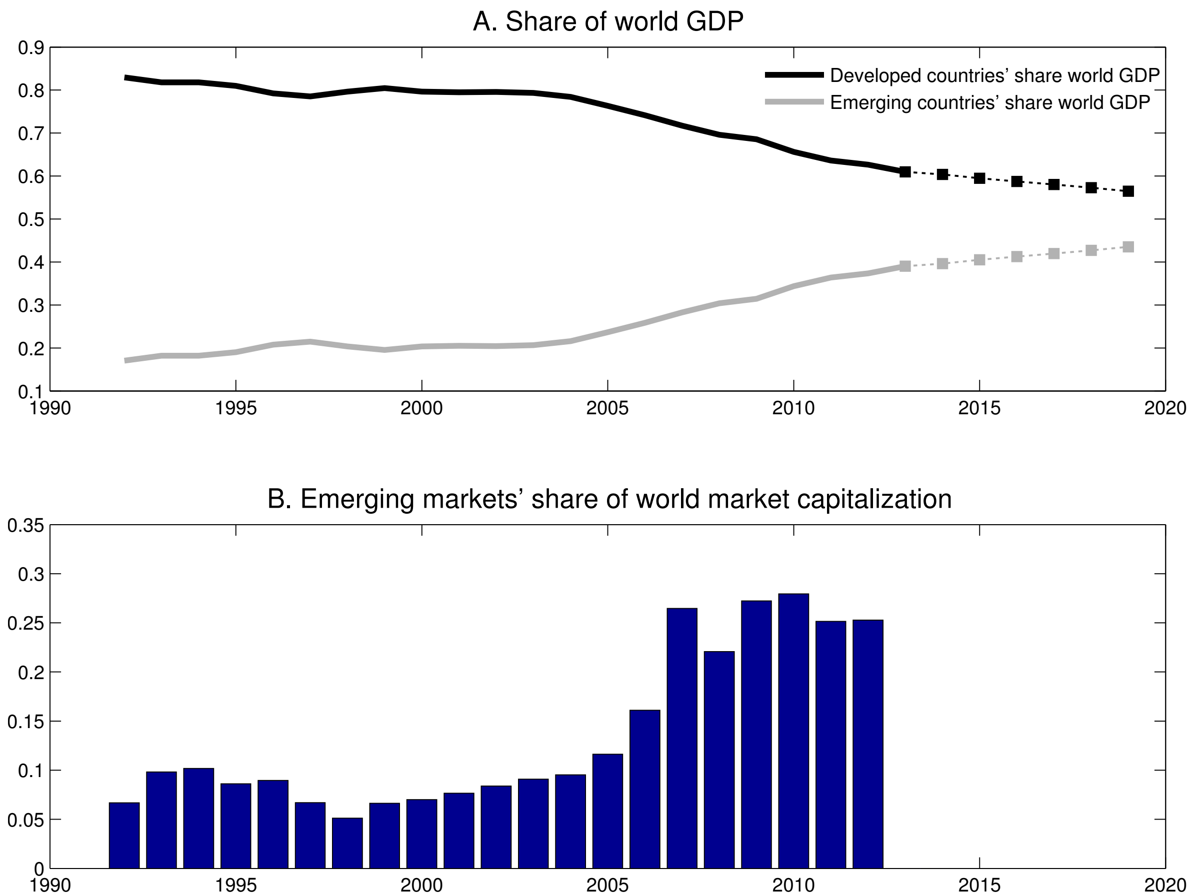

Figure 1. Economic growth and market capitalization of international markets This figure plots in Panel A the proportion of world GDP attributable to developed and emerging markets. Dashed lines indicate projections. Panel B shows the share of world market capitalization attributable to emerging markets. The GDP data are from the International Monetary Fund, and the market capitalization data are from the World Bank. The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey.

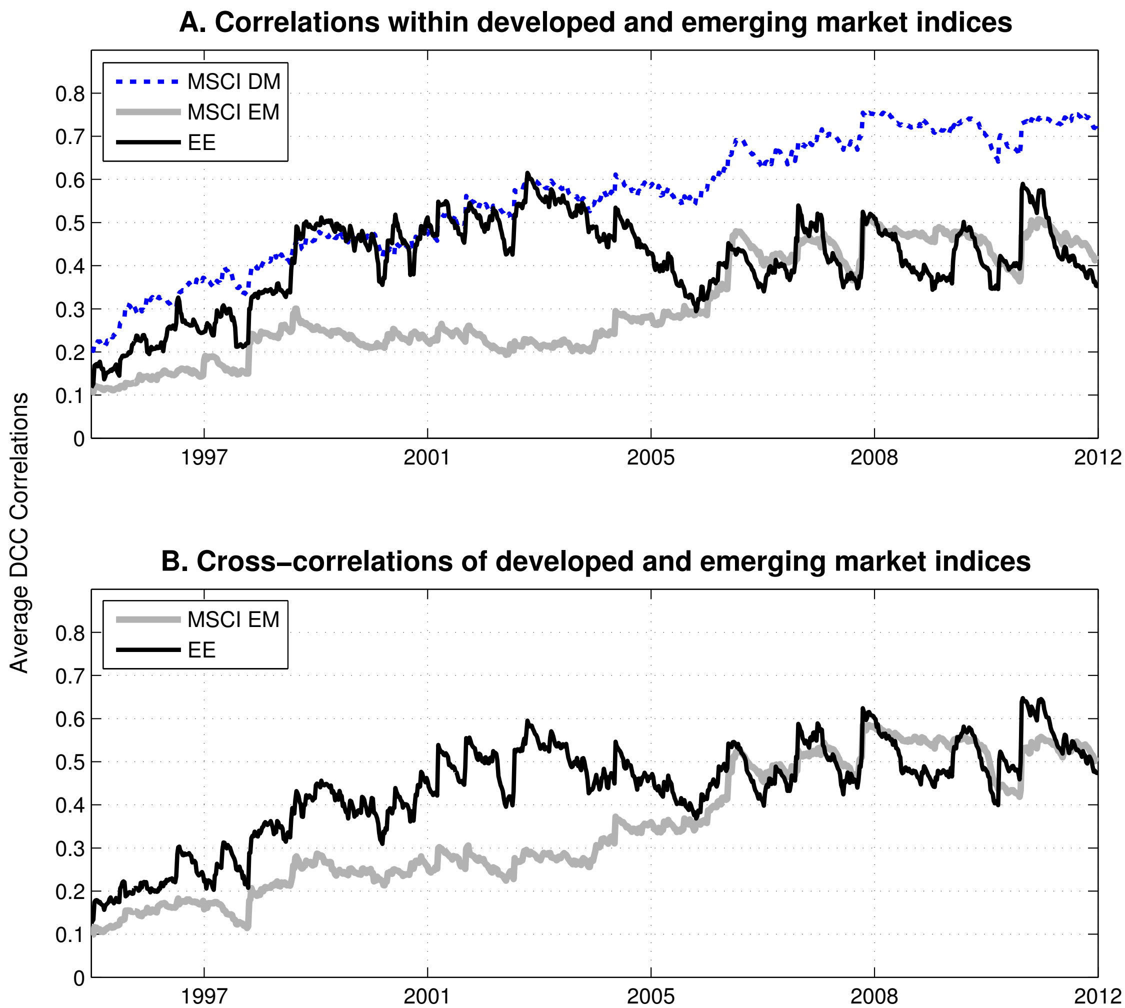

Figure 2. Average DCC model correlations for market indices

This figure plots average correlations for developed market MSCI indices (MSCI DM), emerging market MSCI indices (MSCI EM), and emerging economy indices (EE). Correlations are computed using the dynamic conditional correlation (DCC) model. In panel A, bilateral correlations are computed within the three sets of indices separately. For example, the black line represents average of all bilateral correlations of EE indices. Panel B plots averages of all correlations of developed marker MSCI indices with either emerging market MSCI indices (gray line) or EE indices (black line). The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of EE indices is described in section I.B. The DCC computation methodology is described in the appendix. DCC computations do not allow for missing data, and hence the sample of correlations spans the period from 1996 to 2012.

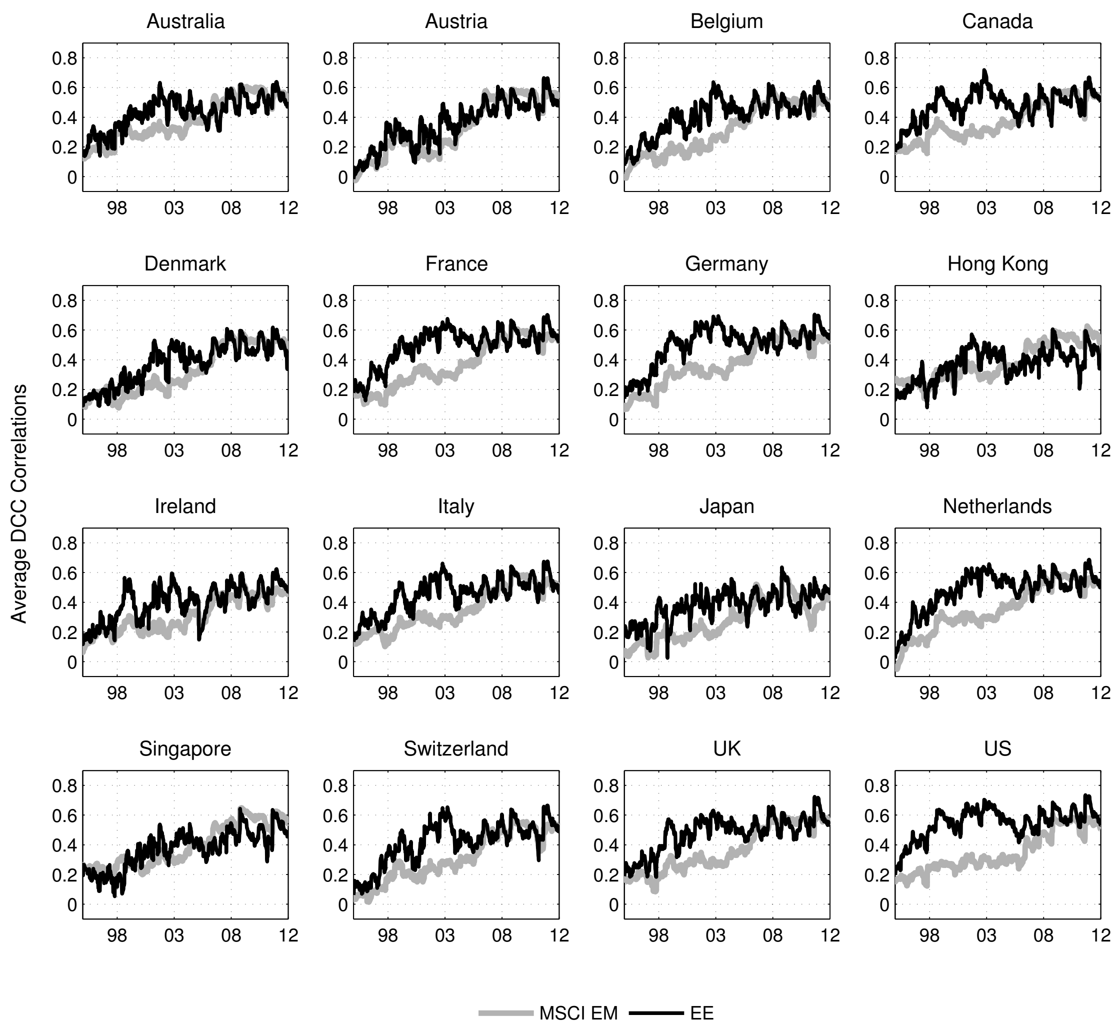

Figure 3. Average DCC model cross-correlations

This figure plots averages of all correlations of the MSCI index of a given developed market with either emerging market MSCI indices (gray line) or EE indices (black line). Correlations are computed using the dynamic conditional correlation (DCC) model. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of EE indices is described in section I.B. The DCC computation methodology is described in the appendix. DCC computations do not allow for missing data, and hence the sample of correlations spans the period from 1996 to 2012.

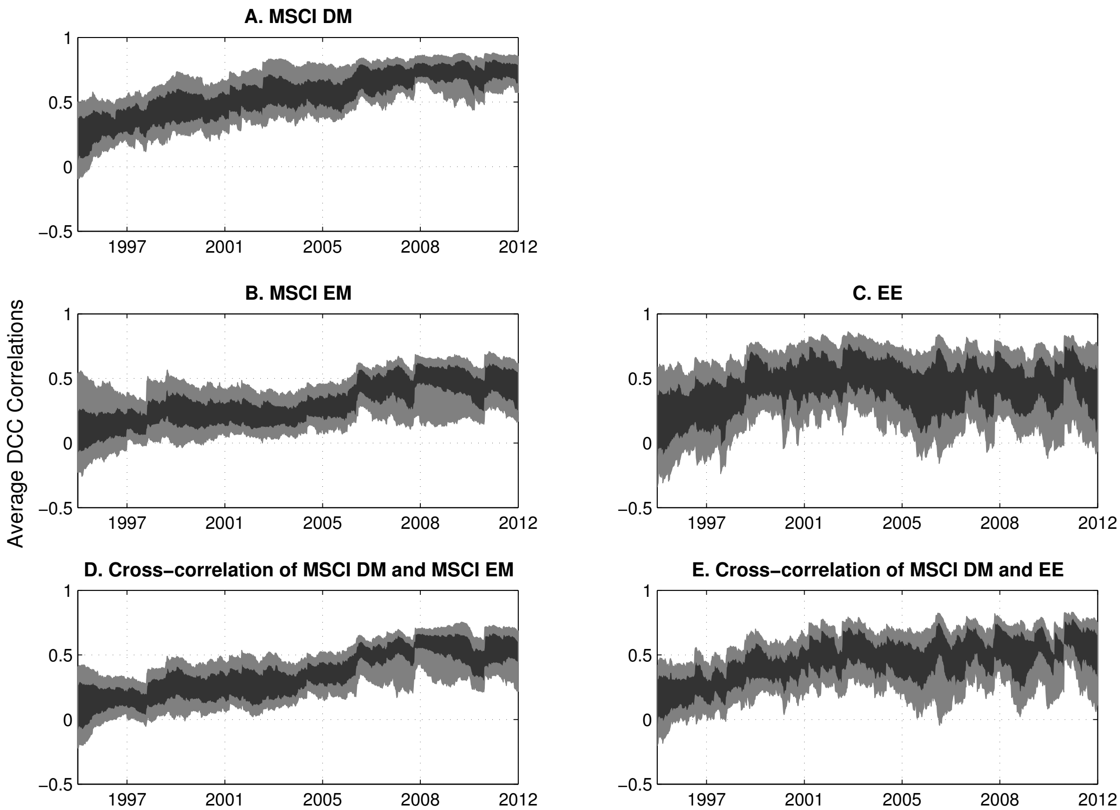

Figure 4. Distribution of DCC model correlations

This figure plots the distribution of correlations for developed market MSCI indices (MSCI DM), emerging market MSCI indices (MSCI EM), and emerging economy indices (EE). Correlations are computed using the dynamic conditional correlation (DCC) model. In panels A through C, bilateral correlations are computed within the three sets of indices separately. Panels D and E show correlations of developed marker MSCI indices with either emerging market MSCI indices or EE indices. The gray area captures the range between 10th and 90th percentiles of correlations, and the black area captures the range between 25th and 75th percentiles. The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of EE indices is described in section I.B. The DCC computation methodology is described in the appendix. DCC computations do not allow for missing data, and hence the sample of correlations spans the period from 1996 to 2012.

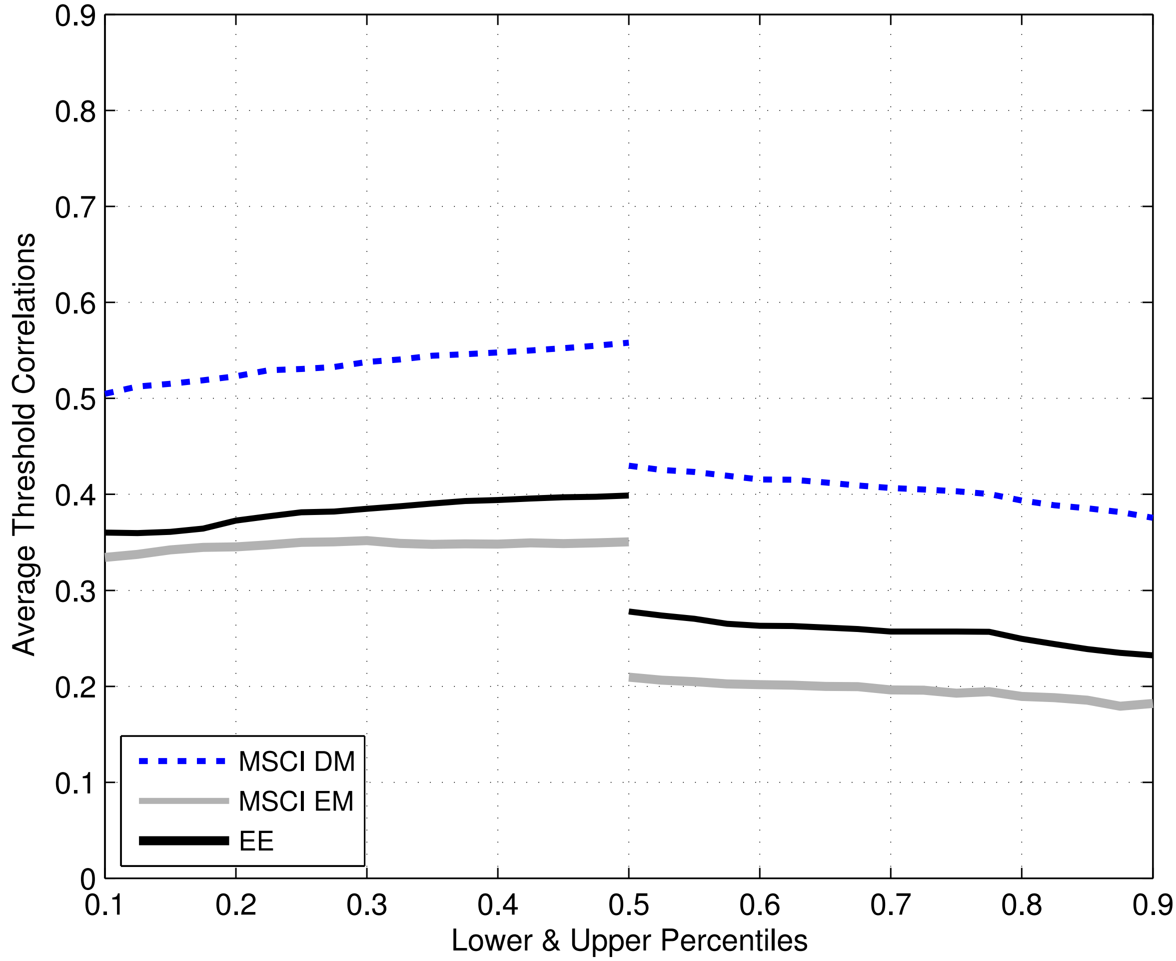

Figure 5. Average pairwise threshold correlations

This figure plots average pairwise threshold correlations, computed on returns that have been standardized by their unconditional means and GARCH(1,1) standard deviations. Pairwise threshold correlation is given by estimating correlation of returns of two countries when both are below (from 0 to 0.5) or above (from 0.5 to 1) the percentile level shown on the x-axis. The blue line represents the average of pairwise threshold correlations within developed market MSCI indices. The gray line shows the corresponding values for emerging market MSCI indices, and the black line shows the correlations for emerging economy (EE) indices. The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of EE indices is described in section I.B. The returns span the period from 1992 to 2012.

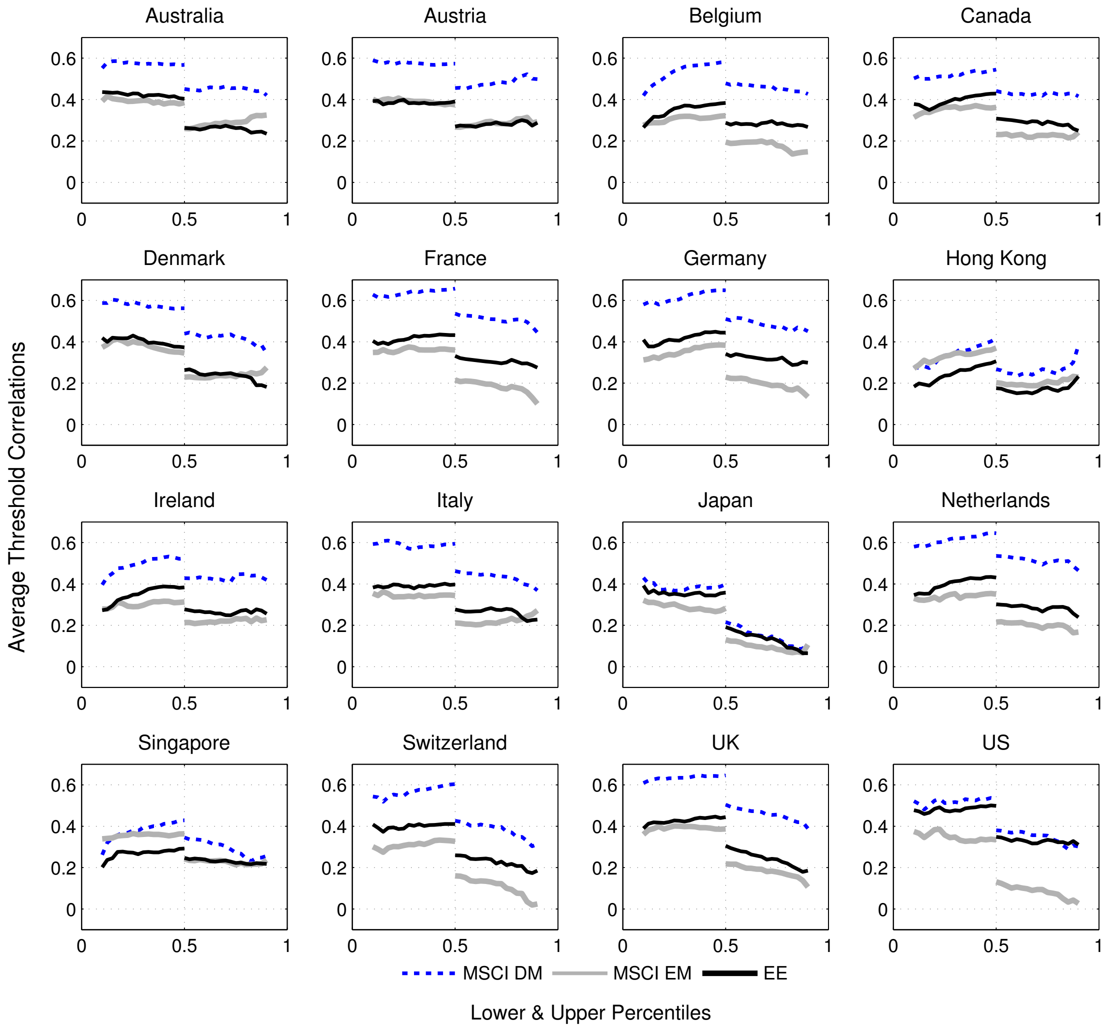

Figure 6. Average pairwise threshold correlations: Individual countries
This figure plots average pairwise threshold correlations between each developed market MSCI index and 20 emerging market indices. Correlations are computed on returns that have been standardized by their unconditional means and GARCH(1,1) standard deviations. Pairwise threshold correlation is given by estimating correlation of returns of two countries when both are below (from 0 to 0.5) or above (from 0.5 to 1) the percentile level shown on the x-axis. The blue line represents the average of pairwise threshold correlations with developed market MSCI indices. The gray and black lines shows the average of all pairwise threshold correlations with emerging market MSCI indices and emerging economy (EE) indices, respectively. The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of EE indices is described in section I.B. The returns span the period from 1992 to 2012.

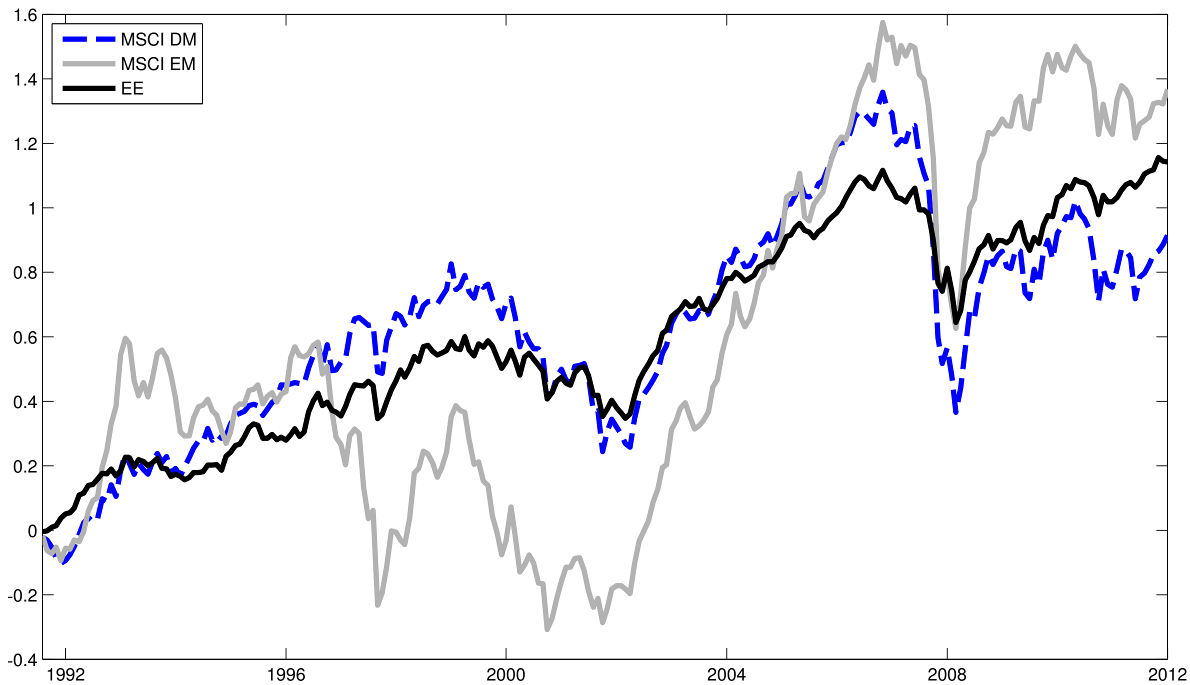

Figure 7. Cumulative returns of developed and emerging market equity indices and emerging economy indices

This figure plots cumulative returns, in decimals, of the portfolio of MSCI indices of developed markets (MSCI DM), of the portfolio of MSCI indices of emerging markets (MSCI EM), and for the portfolio of emerging economy indices (EE). Portfolios are rebalanced to equal weights at the beginning of every year. Emerging economy indices are constructed by investing in export-oriented industries of developed markets as described in section I.B. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The returns span the period from 1992 to 2012.

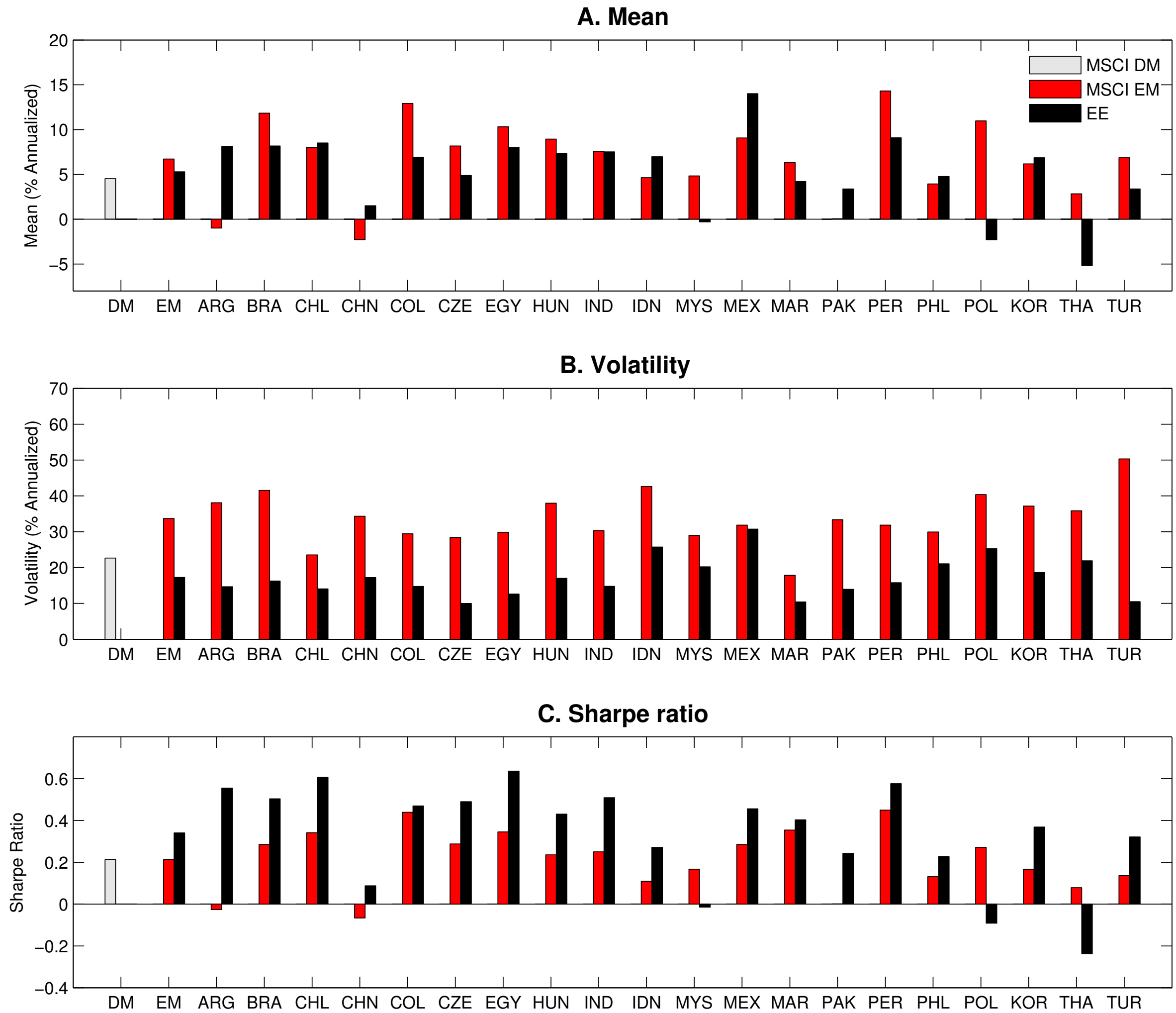

Figure 8. Moments of returns of country portfolios

This figure plots means, volatilities, and Sharpe ratios of returns for an equal-weighted portfolio of MSCI indices of developed markets (first bar, labeled DM), for an equal-weighted portfolios of indices of emerging markets (second set of bars, labeled EM), and for individual emerging countries (the remaining 20 sets of bars). For a given emerging country, results based on two different indices are shown separately: those based on MSCI indices (MSCI EM, red bars) and those based emerging economy indices (EE, black bars). Emerging economy indices are constructed by investing in export-oriented industries of developed markets as described in section I.B. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. Means and volatilities are in percent per year. The returns span the period from 1992 to 2012.

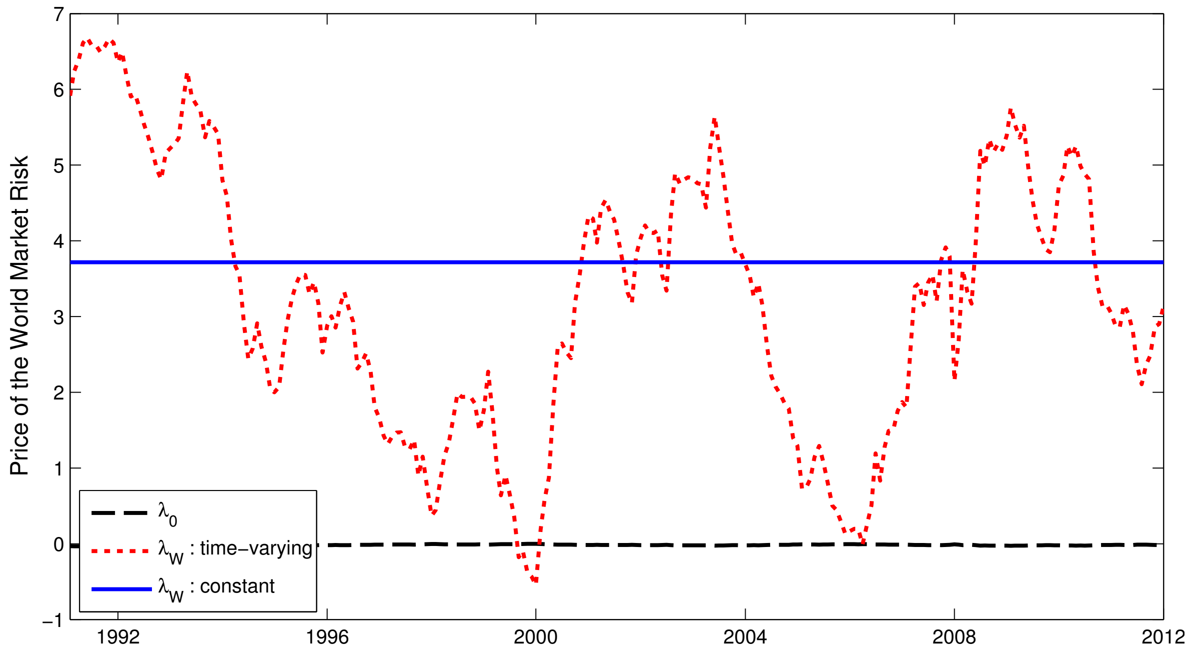

Figure 9. Price of world market risk

This figure plots time-varying price of covariance risk for the world market factor. We use Fama-French global market factor and 25 global portfolios formed on size and book-to-market as our world market factor and test assets, respectively. The dashed black line is the estimated λ_0 and the dotted red line is the estimated λ_W, which is the time-varying price of the world market factor. For comparison, the solid blue line shows the constant price of the world market factor. Estimation details are provided in Section III.A. Price of risk is shown in percent per year. The sample period is 1992-2012.

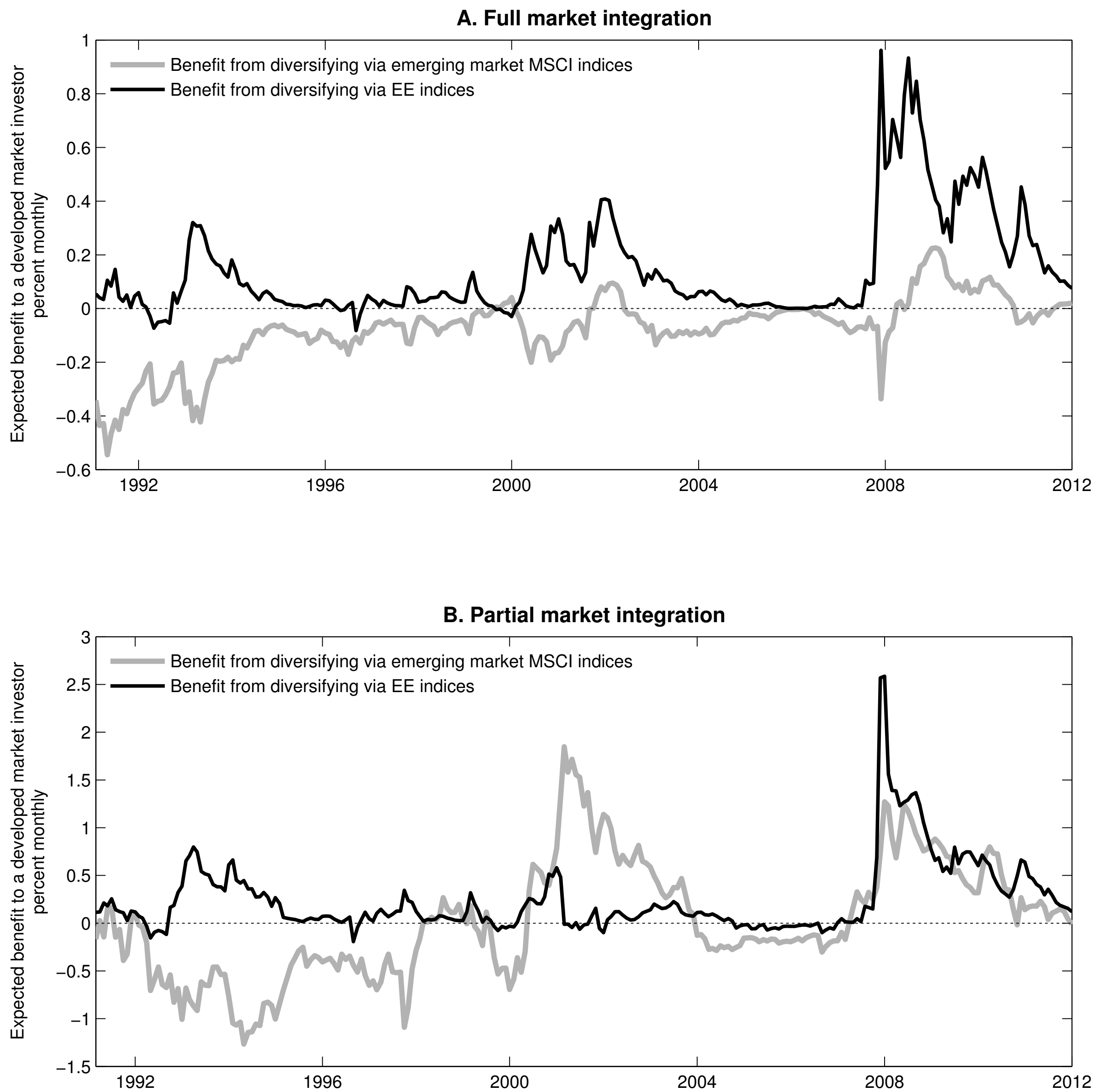

Figure 10. Expected benefits of diversification

This figure plots the benefits an investor in developed market MSCI indices can expect by diversifying into emerging countries via emerging market MSCI indices (gray line) or via emerging economy indices (black line). The benefits are shown in percent monthly. In Panel A, the expected benefits are calculated under the assumption that financial markets are fully integrated and that expected returns are driven by the exposure to the world market portfolio. In Panel B, the expected benefits are calculated under the assumption that financial markets are partially integrated and that expected returns are driven by the exposure to the world market factor and the emerging market factor. Details of estimation under the full integration and partial integration are provided in Sections III.A and III.B, respectively.

Table I
Exports from Developed to Emerging Countries

This table reports average proportion of exports from seven developed countries to 20 emerging countries. Each year, proportions are measured by aggregating exports from the exporting country (column) to the importing country (row) and dividing by sum of exports to the importing country from seven developed countries. Reported are time-series averages of the resulting proportions. The sample period is 1991-2011.

	Developed markets						
Emerging markets	Australia	Canada	France	Germany	Japan	UK	US
Argentina	0.9	1.8	11.9	17.3	8.2	4.9	55.1
Brazil	1.2	3.1	7.5	20.0	10.2	4.8	53.1
Chile	1.5	3.4	7.5	12.6	14.9	3.7	56.3
China	5.6	3.2	4.8	15.0	46.0	2.8	22.7
Colombia	0.2	3.1	5.3	10.1	13.5	2.9	65.0
Czech Republic	0.2	0.4	9.8	75.9	2.9	7.3	3.5
Egypt	1.3	2.1	15.5	23.6	12.8	10.6	34.1
Hungary	0.1	0.4	11.2	69.6	6.8	6.9	5.1
India	11.2	2.6	7.5	18.9	16.8	15.2	27.8
Indonesia	8.5	2.5	4.7	11.4	53.2	3.5	16.1
Malaysia	4.7	1.2	3.8	9.3	46.6	5.3	29.1
Mexico	0.2	1.4	1.6	5.0	5.7	0.9	85.2
Morocco	0.2	1.3	57.2	17.7	4.5	9.3	9.8
Pakistan	3.7	2.1	9.8	17.8	31.1	13.7	21.9
Peru	0.8	3.0	3.7	9.9	13.3	2.9	66.3
Philippines	4.2	1.4	3.2	6.2	50.3	3.0	31.7
Poland	0.1	0.5	13.3	69.4	2.4	9.8	4.5
South Korea	7.0	2.4	3.1	8.1	46.0	2.7	30.7
Thailand	5.2	1.1	3.5	8.0	59.3	3.5	19.4
Turkey	1.0	1.1	16.7	43.8	7.6	12.1	17.6
Average	2.9	1.9	10.1	23.5	22.6	6.3	32.8

Table II
Moments of Returns of Emerging Country Indices

This table reports statistics for returns of the emerging market MSCI indices (left set of columns) and those of the emerging economy indices (EE, right set of columns). Mean excess returns and standard deviations are in percent per year. The construction of the EE indices is described in section I.B. The returns span the period from 1992 to 2012.

	MSCI equity market indices					Emerging economy indices				
	Mean	Stdev	Skew	Kurt	Sharpe	Mean	Stdev	Skew	Kurt	Sharpe
Argentina	-1.0	38.1	-0.3	5.9	-0.03	8.1	14.7	-0.4	5.6	0.55
Brazil	11.8	41.5	-1.1	9.0	0.28	8.2	16.2	-0.5	8.1	0.50
Chile	8.0	23.5	-1.0	13.5	0.34	8.5	14.1	-0.5	5.2	0.61
China	-2.3	34.3	-0.2	5.2	-0.07	1.5	17.2	-0.3	6.5	0.09
Colombia	12.9	29.4	-0.4	7.4	0.44	6.9	14.7	-0.7	7.5	0.47
Czech Republic	8.2	28.4	-0.7	5.9	0.29	4.9	10.0	0.5	11.7	0.49
Egypt	10.3	29.8	-0.5	6.3	0.35	8.0	12.6	-0.7	5.9	0.64
Hungary	8.9	37.9	-0.8	8.5	0.24	7.3	17.0	0.0	19.4	0.43
India	7.6	30.3	-0.2	4.9	0.25	7.5	14.8	-0.5	11.6	0.51
Indonesia	4.6	42.6	-0.8	11.8	0.11	7.0	25.7	-0.3	6.6	0.27
Malaysia	4.8	29.0	-0.7	19.3	0.17	-0.3	20.2	-0.4	6.9	-0.01
Mexico	9.1	31.8	-0.8	9.7	0.29	14.0	30.7	0.5	23.5	0.46
Morocco	6.3	17.9	-0.2	7.1	0.35	4.2	10.4	-0.9	9.0	0.40
Pakistan	0.1	33.4	-0.9	7.8	0.00	3.4	13.9	-1.0	10.8	0.24
Peru	14.3	31.9	-0.3	6.1	0.45	9.1	15.8	-0.6	7.0	0.58
Philippines	3.9	29.9	-0.1	6.7	0.13	4.8	21.0	-0.2	4.8	0.23
Poland	11.0	40.3	-0.3	7.1	0.27	-2.3	25.2	-2.7	39.4	-0.09
South Korea	6.2	37.1	-0.6	9.5	0.17	6.9	18.6	-0.5	8.4	0.37
Thailand	2.8	35.8	0.0	5.6	0.08	-5.2	21.9	-0.3	4.1	-0.24
Turkey	6.9	50.3	-0.6	5.3	0.14	3.4	10.5	-0.1	9.7	0.32

Table III
Moments of Returns of Equally-Weighted Portfolios

This table reports statistics for returns of portfolios created by equally-weighting developed market MSCI indices (MSCI DM), emerging market MSCI indices (MSCI EM), emerging economy indices (EE), both developed and emerging market MSCI indices (MSCI DM + MSCI EM), and both developed market MSCI indices and emerging economy indices (MSCI DM + EE). Panel A shows full-sample moments, and Panels B and C show statistics conditional on U.S. recessionary and expansionary periods, respectively, defined by the NBER. The developed markets are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, Singapore, Switzerland, United Kingdom, and United States. The emerging markets are Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Pakistan, Peru, Philippines, Poland, South Korea, Thailand, and Turkey. The construction of the EE indices is described in section I.B. Mean excess returns and standard deviations are in percent per year. The returns span the period from 1992 to 2012.

				MSCI DM +	
	MSCI DM	MSCI EM	EE	MSCI EM	EE
A. Full-sample moments					
Mean	4.53	6.88	5.29	5.72	4.95
Stdev	17.85	19.33	10.39	17.63	13.19
Skew	-0.87	-1.04	-0.88	-1.05	-0.94
Kurt	8.01	9.10	8.84	9.45	8.83
Sharpe	0.25	0.36	0.51	0.32	0.38
B. Moments during recessionary periods					
Mean	-50.32	-51.48	-19.57	-50.96	-33.24
Stdev	30.26	31.64	17.30	30.34	22.56
Skew	-0.79	-0.99	-0.98	-0.93	-0.94
Kurt	5.47	8.02	7.37	7.07	6.33
Sharpe	-1.66	-1.63	-1.13	-1.68	-1.47
C. Moments during expansionary periods					
Mean	10.10	12.81	7.82	11.47	8.83
Stdev	15.89	17.42	9.35	15.59	11.72
Skew	-0.43	-0.64	-0.44	-0.56	-0.42
Kurt	5.41	5.05	5.09	5.06	5.34
Sharpe	0.64	0.74	0.84	0.74	0.75

Table IV
Alphas of Emerging Economy Indices

This table reports alphas from regressions of excess returns of emerging economy (EE) indices of 20 countries on factors. Factors include either the excess returns of the 7 developed market MSCI indices and the excess return of the emerging market MSCI index of the targeted country (DM 7+EM 1) or the four Fama-French global factors and the excess return of the emerging market MSCI index of the targeted country (FF 4+EM 1). Reported are annualized alphas, in percent, and the t-statistics parentheses. The construction of the EE indices is described in section I.B. The returns span the period from 1992 to 2012.

	Alphas from factor models	
Countries	DM 7+EM 1	FF 4+EM 1
Argentina	8.71 (2.82)	6.32 (1.93)
Brazil	8.93 (2.73)	5.88 (1.70)
Chile	8.17 (2.91)	5.46 (1.85)
China	7.17 (2.50)	1.45 (0.42)
Colombia	10.27 (3.17)	8.19 (2.39)
Czech Republic	7.01 (2.65)	3.86 (1.29)
Egypt	6.48 (2.97)	2.84 (1.24)
Hungary	4.28 (1.90)	2.06 (0.82)
India	9.58 (4.54)	5.47 (2.37)
Indonesia	8.61 (2.45)	2.38 (0.60)
Malaysia	10.27 (3.08)	4.27 (1.15)
Mexico	9.46 (1.69)	8.64 (1.49)
Morocco	4.55 (1.58)	-0.85 (-0.27)
Pakistan	8.32 (3.95)	3.50 (1.48)
Peru	8.82 (2.88)	5.58 (1.71)
Philippines	4.32 (1.39)	-0.28 (-0.08)
Poland	3.33 (1.42)	0.15 (0.05)
South Korea	7.15 (2.54)	1.26 (0.38)
Thailand	2.08 (0.63)	-5.31 (-1.35)
Turkey	7.21 (3.21)	3.66 (1.47)
Average Alpha	7.24 (13.97)	3.23 (4.47)

Table V
Mean-Variance Spanning Tests

This table reports p-values, in decimals, from mean-variance spanning tests. The regression-based likelihood ratio tests are performed assuming normality and the GMM spanning tests are performed assuming conditional heteroscedasticity. The test assets are the MSCI equity indices of individual emerging countries. The benchmark assets are either the seven developed market MSCI indices (DM) alone or six DM indices in combination with the emerging economy (EE) index of the country being studied (6 DMs + 1 EE). Fixing the number of benchmark assets at seven in each test maximizes the probability of not rejecting the mean-variance spanning test. The bottom row reports the numbers of rejections at the 5 percent significance level. The developed markets are Australia, Canada, France, Germany, Japan, United Kingdom, and United States. The construction of the EE indices is described in section I.B, and details of the mean-variance spanning tests are provided in section II.D.1. The returns cover the period from 1992 to 2012.

	Likelihood Ratio Test		GMM Test	
Test Assets	7 DMs	6 DMs + 1 EE	7 DMs	6 DMs + 1 EE
Argentina	0.62	0.62	0.66	0.66
Brazil	0.01	0.02	0.01	0.08
Chile	0.20	0.94	0.29	0.94
China	0.35	0.42	0.31	0.43
Colombia	0.09	0.72	0.11	0.72
Czech Republic	0.07	0.74	0.15	0.79
Egypt	0.20	0.93	0.19	0.94
Hungary	0.01	0.01	0.01	0.01
India	0.32	1.00	0.45	1.00
Indonesia	0.42	0.42	0.49	0.49
Malaysia	0.02	0.30	0.03	0.36
Mexico	0.04	0.49	0.05	0.42
Morocco	0.00	0.00	0.00	0.00
Pakistan	0.00	0.02	0.01	0.04
Peru	0.01	0.91	0.03	0.93
Philippines	0.25	0.45	0.33	0.47
Poland	0.11	0.11	0.12	0.12
South Korea	0.00	0.09	0.01	0.26
Thailand	0.07	0.15	0.09	0.14
Turkey	0.01	0.06	0.02	0.09
No. rejections	9	4	8	3

Table VI
Mean-Variance Step-Down Spanning Tests

This table reports the results of mean-variance spanning tests. The benchmark assets are seven developed market MSCI indices. In the left set of columns the test assets are emerging market MSCI indices, and in the right set of columns the test assets are emerging economy (EE) indices. The GMM spanning tests are performed assuming conditional heteroscedasticity. The first column of the left and right panels shows the p-values of the mean-variance spanning test. The remaining columns show the sample statistics (Alpha and Delta) and p-values of the step-down sequential tests of Kan and Zhou (2012). The distance between two tangency portfolios is tested in the first test, and the distance between two global minimum-variance portfolios is tested in the second test. The bottom row shows the number of rejections at the 5 percent significance level. Total Test, First Test, and Second Test p-values are in decimals. Alphas are in percent per month. The developed markets are Australia, Canada, France, Germany, Japan, United Kingdom, and United States. The construction of the EE indices is described in section I.B, and details of the mean-variance step-down spanning tests are provided in section II.D.2. The returns cover the period from 1992 to 2012.

	Emerging Market MSCI Indices					Emerging Economy Indices				
Test Assets	Total Test	Alpha	First Test	Delta	Second Test	Total Test	Alpha	First Test	Delta	Second Test
Argentina	0.66	-0.58	0.40	-0.09	0.63	0.00	0.77	0.00	0.69	0.00
Brazil	0.01	-0.21	0.69	-0.43	0.00	0.00	1.01	0.00	0.67	0.00
Chile	0.29	-0.06	0.88	0.17	0.07	0.00	0.83	0.00	0.73	0.00
China	0.31	-0.79	0.16	-0.06	0.72	0.00	0.76	0.00	0.38	0.00
Colombia	0.11	0.68	0.25	0.29	0.06	0.00	1.10	0.00	0.81	0.00
Czech Republic	0.15	0.23	0.63	0.28	0.02	0.00	0.66	0.00	0.30	0.00
Egypt	0.19	0.45	0.44	0.25	0.10	0.00	0.68	0.00	0.45	0.00
Hungary	0.01	-0.16	0.76	-0.44	0.00	0.00	0.42	0.03	0.28	0.00
India	0.45	0.10	0.84	0.19	0.13	0.00	0.89	0.00	0.48	0.00
Indonesia	0.49	-0.30	0.71	-0.27	0.20	0.00	0.92	0.01	0.24	0.01
Malaysia	0.03	-0.21	0.70	0.38	0.01	0.00	1.03	0.00	0.49	0.00
Mexico	0.05	0.19	0.65	-0.26	0.01	0.00	0.94	0.07	1.02	0.00
Morocco	0.00	0.53	0.15	0.73	0.00	0.00	0.47	0.05	0.39	0.00
Pakistan	0.01	-0.51	0.52	0.65	0.00	0.00	0.86	0.00	0.42	0.00
Peru	0.03	0.47	0.32	0.36	0.00	0.00	0.96	0.00	0.85	0.00
Philippines	0.33	-0.65	0.22	0.15	0.25	0.00	0.44	0.13	0.41	0.00
Poland	0.12	-0.27	0.62	-0.28	0.04	0.00	0.40	0.06	0.27	0.00
South Korea	0.01	0.05	0.93	-0.49	0.00	0.00	0.66	0.01	0.55	0.00
Thailand	0.09	-0.71	0.26	-0.33	0.04	0.00	0.21	0.50	0.39	0.00
Turkey	0.02	0.07	0.93	-0.67	0.00	0.00	0.65	0.00	0.29	0.00
No. of rejections	8		0		12	20		15		20

Table VII
Certainty-equivalent Returns

This table reports the incremental changes in certainty-equivalent returns for the expected utility of a mean-variance investor with exponential utility. The changes in certainty-equivalent rates can be interpreted as the amount of risk-free return that an investor would be willing to give up in exchange for having the emerging economy (EE) index in the benchmark portfolio, the seven developed market (DM) MSCI indices. Annualized gains in the certainty-equivalent rate are shown for investors with risk aversion coefficients (γ) of 2, 4, 6 and 8.

	Annualized gains in certainty equivalent rate, %			
Risk Aversion (γ)	2	4	6	8
Argentina	3.21	4.18	5.12	6.07
Brazil	6.32	7.28	7.96	8.72
Chile	3.51	4.70	5.76	6.84
China	1.70	2.19	2.75	3.26
Colombia	5.76	6.61	7.46	8.45
Czech Republic	3.88	3.12	2.66	2.43
Egypt	3.77	4.84	5.61	6.30
Hungary	1.18	1.19	1.29	1.35
India	5.75	6.64	7.23	7.73
Indonesia	2.36	2.16	2.24	2.34
Malaysia	3.26	3.67	4.23	4.84
Mexico	2.08	2.77	3.54	4.30
Morocco	0.86	1.14	1.42	1.64
Pakistan	4.25	5.16	5.78	6.42
Peru	4.33	5.44	6.55	7.70
Philippines	0.00	0.34	0.88	1.43
Poland	1.07	0.92	0.92	0.90
South Korea	1.16	2.27	3.37	4.41
Thailand	0.00	0.01	0.29	0.70
Turkey	4.16	3.98	3.61	3.45
Average	2.93	3.43	3.93	4.46

Table VIII
Changes in Sharpe Ratio of Optimal Tangency Portfolio

This table reports changes in Sharpe ratios associated with the addition of an emerging country index to the benchmark portfolio containing MSCI indices of the seven developed markets. The results are shown for two sets of emerging country indices: emerging market MSCI indices (MSCI EM) and emerging economy (EE) indices. The developed markets are Australia, Canada, France, Germany, Japan, United Kingdom, and United States. The monthly returns span the period from 1992 to 2012.

Test Assets	MSCI EM	EE
Argentina	0.000	0.077
Brazil	0.000	0.139
Chile	0.000	0.091
China	0.000	0.034
Colombia	0.017	0.130
Czech Republic	0.001	0.059
Egypt	0.007	0.091
Hungary	0.000	0.021
India	0.000	0.125
Indonesia	0.000	0.036
Malaysia	0.000	0.063
Mexico	0.000	0.046
Morocco	0.020	0.016
Pakistan	0.000	0.095
Peru	0.012	0.111
Philippines	0.000	0.000
Poland	0.000	0.018
South Korea	0.000	0.035
Thailand	0.000	0.000
Turkey	0.000	0.070
Average	0.003	0.063

Table IX
Mean-Variance Step-Down Spanning Tests: Individual Developed Countries

This table reports the results of mean-variance spanning tests. For each developed country, Panel A studies the benefits of adding an emerging economy (EE) index constructed using only investments in that developed country ("locally-constructed EE index") to the benchmark portfolio containing the MSCI index of that country ("local MSCI index"). For each developed country, Panel B studies the benefits of adding an EE index constructed using investments in all seven developed market ("globally-constructed EE index") to the benchmark portfolio containing the local MSCI index and the locally-constructed EE index. The GMM spanning tests are performed assuming conditional heteroscedasticity. The first numeric column shows the p-values of the mean-variance spanning test. The remaining columns show the sample statistics (Alpha and Delta) and p-values of the step-down sequential tests of Kan and Zhou (2012). The distance between two tangency portfolios is tested in the first test, and the distance between two global minimum-variance portfolios is tested in the second test. Total Test, First Test, and Second Test p-values are in decimals. Alphas are in percent per month. The developed markets are Australia, Canada, France, Germany, Japan, United Kingdom, and United States. The construction of EE indices is described in section I.B, and details of the mean-variance step-down spanning tests are provided in section II.D.2. The returns cover the period from 1992 to 2012.

Developed Country	Total Test	Alpha	First Test	Delta	Second Test
A. Adding the locally-constructed EE index to the local MSCI index					
Australia	0.00	0.34	0.00	0.61	0.00
Canada	0.00	0.23	0.00	0.62	0.00
France	0.00	0.38	0.00	0.71	0.00
Germany	0.00	0.22	0.00	0.71	0.00
Japan	0.00	0.50	0.04	0.51	0.00
United Kingdom	0.00	0.32	0.01	0.53	0.00
United States	0.00	0.58	0.01	0.11	0.00
B. Adding the globally-constructed EE index to the local MSCI index and the locally-constructed EE index					
Australia	0.00	0.52	0.05	0.69	0.00
Canada	0.00	0.32	0.17	0.68	0.00
France	0.00	0.49	0.02	0.50	0.00
Germany	0.00	0.44	0.03	0.51	0.00
Japan	0.00	0.61	0.01	0.87	0.00
United Kingdom	0.00	0.43	0.03	0.45	0.00
United States	0.00	0.08	0.12	0.52	0.00

Table A.I
Average Short-selling in Emerging Economy Portfolios

This table summarizes short-selling involved in constructing the emerging economy portfolios. Panel A shows the average fraction of industries that are short-sold. Panel B shows the average portfolio weights conditional on short-selling. The returns span the period from 1992 to 2012.

	Developed markets							
Emerging markets	Australia	Canada	France	Germany	Japan	UK	US	Average
A. Average fraction of industries short-sold (%)								
Argentina	15.0	13.4	17.8	15.9	23.4	22.8	14.9	17.6
Brazil	14.6	11.4	22.2	20.8	31.6	17.1	12.7	18.6
Chile	14.2	12.0	15.8	23.3	32.4	18.0	13.7	18.5
China	11.7	11.3	26.0	32.4	25.4	20.1	14.2	20.2
Colombia	11.7	12.3	16.1	13.2	23.3	18.2	15.2	15.7
Czech Republic	11.8	12.7	16.9	22.6	35.3	13.1	13.8	18.0
Egypt	14.2	11.9	25.4	17.9	44.8	18.1	14.4	21.0
Hungary	11.4	13.0	17.3	15.8	26.1	24.2	13.4	17.3
India	14.8	11.8	18.4	18.5	26.2	13.5	13.3	16.6
Indonesia	12.1	11.7	23.2	12.8	47.4	14.4	13.6	19.3
Malaysia	14.2	12.7	22.4	13.1	41.1	13.3	14.9	18.8
Mexico	11.7	11.6	18.0	12.6	37.0	20.9	15.3	18.2
Morocco	12.7	11.4	12.0	11.7	26.9	13.1	12.7	14.4
Pakistan	11.7	11.5	15.4	11.7	22.8	29.1	13.5	16.5
Peru	11.9	12.1	21.2	15.5	44.8	17.3	13.7	19.5
Philippines	13.2	11.3	22.1	18.3	32.3	13.5	13.0	17.7
Poland	11.6	12.2	16.0	24.6	25.5	19.7	14.7	17.8
South Korea	18.9	11.8	15.9	12.5	55.5	16.0	14.1	20.7
Thailand	11.7	12.5	28.1	14.7	24.1	16.6	13.9	17.4
Turkey	13.4	11.3	20.1	12.1	29.4	16.8	12.7	16.6
Average	13.1	12.0	19.5	17.0	32.8	17.8	13.9	18.0
B. Average portfolio weights conditional on short selling (%)								
Argentina	-3.7	-0.9	-1.7	-6.0	-11.0	-2.2	-4.9	-4.3
Brazil	-5.9	-0.9	-2.8	-4.5	-9.4	-3.9	-3.3	-4.4
Chile	-2.7	-0.5	-3.4	-2.6	-5.3	-3.7	-2.9	-3.0
China	-5.4	-1.5	-2.2	-1.9	-4.4	-3.4	-5.5	-3.5
Colombia	-1.3	-1.6	-4.3	-5.1	-9.0	-3.3	-2.6	-3.9
Czech Republic	-1.6	-0.7	-4.1	-2.1	-4.9	-5.3	-1.7	-2.9
Egypt	-4.0	-1.1	-2.7	-3.8	-5.0	-1.9	-1.7	-2.9
Hungary	-1.7	-0.4	-4.2	-6.7	-7.0	-3.1	-1.8	-3.5
India	-5.8	-0.6	-2.9	-4.2	-9.2	-4.4	-3.5	-4.4
Indonesia	-1.9	-1.3	-2.4	-3.1	-5.0	-3.9	-1.8	-2.8
Malaysia	-5.1	-1.1	-2.3	-3.5	-5.5	-4.8	-6.0	-4.0
Mexico	-5.1	-1.5	-3.6	-8.4	-5.6	-3.6	-8.7	-5.2
Morocco	-2.5	-0.3	-1.6	-3.3	-8.5	-1.0	-0.9	-2.6
Pakistan	-4.8	-0.4	-2.8	-4.0	-8.9	-2.1	-1.5	-3.5
Peru	-3.3	-1.0	-2.1	-3.2	-3.9	-2.5	-3.5	-2.8
Philippines	-2.1	-1.0	-2.0	-3.0	-6.6	-3.4	-3.0	-3.0
Poland	-1.7	-0.7	-4.1	-6.6	-8.6	-3.3	-1.8	-3.8
South Korea	-5.9	-2.0	-4.0	-8.2	-2.4	-4.2	-4.2	-4.4
Thailand	-10.0	-1.0	-2.4	-6.4	-11.0	-3.2	-4.9	-5.6
Turkey	-6.4	-0.8	-3.2	-6.8	-8.0	-4.4	-2.0	-4.5
Average	-4.0	-1.0	-2.9	-4.7	-7.0	-3.4	-3.3	-3.8

Table A.II
Robustness Tests

This table reports the results of three tests performed using alternative emerging economy (EE) indices of 20 countries. The alternative EE indices include portfolios constructed by (i) re-defining the industry set from two-digit SIC codes to 17 industries classified on Ken French's data library, (ii) using expected exports forecasted from an autoregressive model, and (iii) requiring no short-selling in the construction of the EE portfolios. Panel A reports alphas from regression of excess returns of EE indices of 20 countries on factors. Factors include either the excess returns of the 7 developed market MSCI indices and the excess return of the emerging market MSCI index of the targeted country (DM 7+EM 1) or the four Fama-French global factors and the excess return of the emerging market MSCI index of the targeted country (FF 4+EM 1). Reported are average annualized alphas, in percent, and the t-statistics parentheses. Panel B reports the results of the mean-variance step-down spanning tests. Each row shows the number of rejections at the 5 percent significance level from the total test, the first test, and the second test. The distance between two tangency portfolios is tested in the first test, and the distance between two global minimum-variance portfolios is tested in the second test. The remaining columns show the sample statistics: the average alpha in percent monthly and the average delta. The returns span the period from 1992 to 2012.

A. Average alphas

	DM 7 + EM 1		FF 4 + EM 1	
Fama-French 17 industries	4.16	(3.15)	2.44	(1.91)
Forecasted export	1.73	(2.79)	2.25	(3.40)
No short-selling	2.34	(6.17)	2.23	(4.89)

B. Mean-variance step-down spanning tests, number of rejections

	Total Test	Average Alpha	First Test	Average Delta	Second Test
Fama-French 17 industries	10	0.37%	7	0.12	8
Forecasted export	20	0.24%	4	0.39	19
No short-selling	20	0.29%	13	0.39	20