Market Segmentation and International Diversification Across Country and Industry Portfolios

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Abstract

We conjecture that partially segmented stock indexes that are characterized by low correlation with the world market are mainly priced by local factors and should produce abnormal returns relative to a global asset-pricing model. This implies a negative relation between correlation and future index returns in the presence of segmented indexes. Empirical evidence confirms such a relationship for the sample of industry indexes, suggesting a heterogeneous segmentation. However, we do not observe a similar pattern for country indexes. In addition, the international diversification potential of industries does not vanish during volatile periods. The hypothesis that the negative relationship should be stronger for the more segmented subsamples that are characterized by small market size and emerging country origin is verified for the industry sample. Thus, cross-industry diversification is superior to mere cross-country diversification.

JEL Classification Codes: G11, G12

Keywords: International portfolio diversification, Industry diversification, Country diversification, Partial segmentation and integration, Index return correlations

1. Introduction

Investing in country indexes or industry indexes in multiple countries can help investors diversify internationally. This raises the research question of which diversification strategy, cross-country or cross-industry, is more beneficial for global investors. There is a long-lasting debate on this issue. On the one hand, several studies document that country-specific factors contribute more to the variation in asset returns than industry-specific factors do (Heston & Rouwenhorst, 1994; Griffin & Karolyi, 1998; Ehling & Ramos, 2006; Campa & Fernandes, 2006). According to these studies, country effects are the main drivers of international asset returns and thus, the cross-country diversification is more important. On the other hand, Roll (1992) disagrees with this view and argues that the correlation structure among countries, which determines the diversification potential of cross-country investing, is driven by the industry orientation of each country. Hence, diversifying along industries should be relatively more important. Numerous studies support this argument and try to explain why cross-industry diversification might gain importance against cross-country diversification (Baca et al., 2000; Cavaglia et al., 2000; Ferreira & Gama, 2005; Phylaktis & Xia, 2009). Given the two opposite lines of view on the relative importance of cross-country and cross-industry diversification, more empirical evidence is needed in order to clarify this issue.

In this study, we follow a different route to assess the relative importance of industry and country effects in international diversification from the perspective of partial market segmentation theories. If there are country or industry indexes that have significantly low return correlations with the world market index (and are, therefore, more segmented), then those index returns should be mainly driven by local factors rather than global factors. We conjecture that indexes with low correlations should produce larger alphas from a global asset pricing model. This assertion follows from the fact that expected returns are higher in segmented markets and that they tend to decrease in the transition from a segmented market to an integrated market (Chari & Henry, 2004; De Jong & De Roon, 2005). A low-correlation segmented index that is locally priced posits a higher expected return than the expected return commanded by a global asset-pricing model. This is because expected returns in a global setting are lower due to risk sharing with international investors. Hence, the expected return on a segmented index will lie above the security market line or plane generated by a global asset pricing model and produce a positive alpha. This implies a negative relation between correlation and future index returns; i.e., the lower the correlation (the higher the degree of segmentation) of an index, the higher the future index returns.

We test this conjecture by examining whether a trading strategy that goes long partially segmented industries characterized by low correlations with the world market and shorts partially integrated industries with high correlations produces positive alphas relative to a global asset-pricing model. We repeat the same exercise with country indexes to shed light on whether alphas only exist or are stronger in the universe of industry indexes. If country indexes became much more integrated (as asserted in the literature) and, thus, became more correlated with the world market during the globalization process, then country indexes should be dominantly priced by global factors. Therefore, an asset-pricing model with global factors will leave no alpha in returns of country indexes, suggesting no relation between country correlation and future country returns. Moreover, if country indexes end up with similar levels of correlations during the globalization process, then sorting country indexes based on correlations should not produce remarkable cross-sectional variation in correlations across country indexes. Therefore, a correlation-based trading strategy that is applied in the universe of country indexes might not have the power to predict country returns.

< Insert Figure 1 here >

Our key conclusions are illustrated by Figure 1. In the industry index universe, a long-short trading strategy based on the one-way sort of sample correlation yields equal-weighted returns that are significantly larger than those produced in the country index universe. An industry-based long-short correlation portfolio offers a monthly raw return of 0.67%. It also delivers monthly risk-adjusted returns (alphas) of 0.92% and 0.89% from the global versions of Fama and French (1993) three-factor model (FF3) and the Fama and French (2015) five-factor model extended by the Carhart's (1999) momentum factor (FFC6), respectively. Country-based raw return and alphas from the global FF3 and FFC6 models are 0.10%, 0.29%, and 0.18%, respectively, which are considerably lower than their industry-based counterparts. More importantly, none of the returns on the country-based long-short correlation portfolio significantly deviates from zero, as will be further described in the results section. In contrast to country-based returns, all industry-based returns positively and significantly deviate from zero. These preliminary findings offer solid confirmation of our conjecture that indexes that are weakly correlated with the world market should leave positive alphas from a global asset pricing model.

Our additional results and robustness tests can be summarized as follows. The graphical analysis of the time-series of average industry and country correlations shows that industry correlations are lower. This supports the literature stating that industry correlations remained smaller when compared to country correlations. Furthermore, the analysis of the coefficient of variation ratios indicates that industry correlations exhibit remarkable cross-sectional variation, whereas country correlations are relatively uniform. As a result, the degree of segmentation/integration is heterogeneous across industry indexes but is homogenous for country indexes. These preliminary analyses indicate that cross-industry diversification allows for bringing together heterogeneously segmented industry indexes with varying levels of correlations in an international portfolio. Analyses of the portfolio sorts show that the long-short portfolios based on the sample and implied correlations leave significant positive alphas in *industry* returns. This suggests a negative cross-sectional relationship between correlation measures and future return. Cross-sectional regressions confirm this relationship for industry indexes, after controlling for a wide set of return predictors. However, neither the portfolio-level analyses nor the predictive regressions point out a significant relation between correlation and returns for country indexes. Hence, investing across segmented industries—as opposed to countries—provides profit opportunities for global investors.

The other research question that we address is whether the benefits of international diversification evaporate when they are most needed. To answer this question, we examine whether international diversification potential persists during turbulent times. We conduct a sub-period analysis based on high- and low-volatility months, which are classified according to the median of monthly return volatilities of the world market index. We demonstrate that index return predictability for segmented industries prevails, even during turbulent times. This result undermines the view that international diversification loses its value when it is most needed.

Last, we perform subsample analyses to check the robustness of our results. The conjecture that there is a negative relationship between index correlations and future index returns for segmented indexes provides further testable implications. If such a relationship holds in the presence of heterogeneously segmented indexes, then this relationship should be more pronounced for small indexes and indexes from emerging markets that are expected to display a more segmented nature. To test these implications, we first conduct bivariate sorts that are based on size and correlation in order to test whether size plays a role in the relationship between correlation and returns. Then, we split the sample into emerging and developed markets and re-run return predictive regressions for correlation measures. Finally, we directly split our sample into segmented and integrated markets by using the segmentation measure developed by Bekaert et al. (2011). The results from the subsample analyses reveal that the negative relationship between correlation and future returns is more pronounced for small industry indexes and industry indexes from emerging markets, which are characterized by a high degree of segmentation. Furthermore, we obtain consistent results for the alternative segmentation measure of Bekaert et al. (2011).

To the best of our knowledge, this is the first study that aims to compare the relative importance of cross-industry and cross-country diversification in the context of partial market integration/segmentation theories. For this purpose, we examine the performance of long-short portfolios based on correlations for the universes of industry and country indexes. We are the first to offer the use of positive alphas from global asset-pricing models as a tool to detect segmented indexes. Moreover, we add to the literature by using two different correlation measures as potential indicators of the degree of market segmentation/integration. These measures are the sample correlation and implied correlation from the global version of the Fama and French (1993) three-factor model. Asness et al. (2020) also document that a trading strategy that bets against sample correlation yields significant alphas in the cross-section of stock returns. Our study complements their work by examining the profitability of correlation-based strategies at both the industry- and country-index levels, which has implications for the relevancy of alternative diversification policies. This study also differs from Asness et al. (2020) and some other studies, such as Pirgaip et al. (2021) and Bali and Cakici (2010), in employing different correlation measures. Our study is also related to the work of Pollet and Wilson (2010), which not only hypothesized that average pairwise correlations can act as a proxy for the aggregate risk but also showed that average correlations predict stock market returns in a domestic setting. We examine the predictive ability of index correlations with the world market for industry and country returns, yielding some inferences about channels for a more powerful international diversification. This issue was not addressed in Pollet and Wilson (2010).

The remainder of the paper is organized as follows. Section 2 surveys the literature. Section 3 describes the data and variables. Section 4 explains the methodology. Section 5 presents the results from portfolio sorts, cross-sectional regressions, sub-period, and subsample analyses. The final section provides the concluding remarks.

2. Literature Review

There are two opposite views on whether diversifying across countries or industries is more important for international portfolio diversification. A line of research that was pioneered by Heston and Rouwenhorst (1994) emphasizes that country effects dominate industry effects in explaining asset returns (Griffin & Karolyi, 1998; Ehling & Ramos, 2006; Campa & Fernandes, 2006). The key implication of these studies for international diversification is that investing across countries, as opposed to industries, will reduce risk more as country-specific effects, which are the main source of variation in asset returns, can be diversified away through country diversification.

The opposite camp is led by Roll (1992), who discusses that countries with similar (different) industry compositions have high (low) pairwise return correlations. Therefore, it is the industry concentration that makes country indexes either move together or independently. As a result of this, cross-industry diversification matters more. In line with this view, Baca et al. (2000), Cavaglia et al. (2000), and Ferreira and Gama (2005) document the increasing importance of industry factors relative to country factors in explaining variations in asset returns. Moreover, Phylaktis and Xia (2009) discuss that cross-country diversification performs poorly during bear markets, as contagion prevails at the country level. However, some sectors (especially counter-cyclical ones) can increase their profitability, even in crisis periods. This is because of the heterogeneous response of sectors to aggregate shocks (Balcilar et al., 2015). It is also argued that market integration erodes the benefits of international diversification across countries. However, industry correlations remained relatively low due to distinct characteristics of industries (Bekaert et al., 2009; Leal & Ratner, 2005). Even the common industries in multiple countries may have low correlations if industrial integration is not fully completed (Umutlu & Bengitöz, 2020; 2021).

Within the literature, various metrics are used to evaluate the relative importance of industry and country effects. Eiling et al. (2012a) employed the ratio of average country-specific return variance over average industry-specific return variance. If countries become more integrated, the country-specific variance will be less important with respect to the industry-specific variance, and so the variance ratio will be less than one. Conversely, if country factors dominate asset returns, then the variance ratio will exceed one. Baele and Inghelbrecht (2009) focus on two indicators of diversification potential, which are asset-specific volatilities and model-implied correlations, to evaluate the relative benefits of country and industry diversification. Eiling et al. (2012b) showed that actively rebalanced industry portfolios outperform country portfolios in terms of their Sharpe ratio. Ratner and Leal (2005) used correlation as a key factor in a portfolio optimization model and have provided evidence in favor of the superiority of sector-based diversification to country-based diversification. By employing model-dependent and model-independent measures of correlation, Umutlu and

Yargı (2022) found that average industry correlation is lower than average country correlation and concluded that diversifying across industries is more effective. Following a modified version of the Heston and Rouwenhorst's (1994) dummy variable representation of country and industry effects in asset returns, Flavin (2004) showed that industry factors increasingly affect stock returns. Accordingly, industrial—rather than geographical— diversification was recommended. Last, Bessler et al. (2021) employed Sharpe and Omega ratios as well as alphas in order to compare the performance of industry- versus country-based asset allocations. They found that industry allocation outperforms country allocation. They reported that countries become more integrated and highly correlated than industries, resulting in lower country and higher industry diversification benefits.

In none of the aforementioned studies, the special role of alpha as a determinant of heterogeneously segmented indexes is investigated in the context of partial market segmentation/integration theories. Detecting heterogeneously segmented indexes is important from the global investors' point of view, as such indexes can improve the extent of international diversification. This study aims to fill this gap within the literature.

3. Data

3.1. Data and Sample

We have two samples consisting of local industry indexes and country indexes. We use Datastream (DS) Global Equity Indexes in order to track industries and countries. A total of 19 industry indexes from each of the 63 countries make up the industry sample. 63 country indexes form the country sample. A local industry index refers to one of the 19 industry indexes in a certain country. Not every industry index exists in each country for every month in the research period. Table A1 in the Appendix lists the non-existent industries by country as well as the countries that were included in the study. Industry groupings are in accordance with the Industry Classification Benchmark of FTSE. The 19 industry groupings used in this study are automobiles and parts, banks, basic resources, chemicals, construction and materials, financial services, food and beverage, health care, industrial goods and services, insurance, media, oil and gas, personal and household goods, real estate, retail, technology, telecommunications, travel and leisure, and utilities. A total of 24 of the 63 countries used in the sample are developed countries. The remaining 39 countries are emerging.

Daily total return series, which are adjusted for dividends and splits and are denominated in U.S. dollars, are downloaded for both industry and country indexes. To calculate the sample correlation between an index and the global market portfolio, we download the daily return on the DS World Market Index. To calculate the implied correlations from the global version of the Fama and French (1993) three-factor model, we also download the three factors from Kenneth French's data library for international markets. These factors are only available from July 1990, which sets the starting date of the research period. The end date is October 2018. To proxy for risk-free interest rates, we use one-month U.S. Treasury Bill rates that are also downloaded from Kenneth French's data library.

3.2. Variable Construction

In addition to return data, we also collect data on several index characteristics as control variables that have the potential to influence returns in regression analyses. These variables can be defined as follows. *EBITDA/EV* indicates the ratio of earnings before interest taxes depreciation and amortization to enterprise value. *MV* is the market value of an index measured as the monthly market capitalization in billion dollars. *ROE* stands for the return on equity. *EP* shows the earnings-to-price ratio. *OP* is operating profitability and is calculated as the difference between *EBIT* and interest payments, divided by book equity. Following Fama and French (2015), we calculate *OP* using the data from the previous year's June and keep *OP* fixed until next June. *INV* refers to investments and is calculated as the change in total assets from June of the year T-2 to June of year T-1, divided by total assets in June of year T-2. Again, in the spirit of Fama and French (2015), *INV* remains constant for the months of the year extending from the previous year's June to the June of the current year. Net share issues (*NSI*) is the net change in shares outstanding and is computed as $Ln(MV_{i,t} \,/\, MV_{i,t-k}) - Ln(PI_{i,t} \,/\, PI_{i,t-k})$ over k months, as Fama and French (2008) suggests. Here, *Ln* represents the natural logarithm, *MV* is the market value of index i in month t, and *PI* is the price index. *MOM* denotes the momentum calculated as the cumulative return over the last 12 months. Idiosyncratic volatility (*IVOL*) is the monthly residual volatility where residuals are obtained from the World CAPM, in which daily index returns are regressed on the return of the world market index.

We use two different correlation measures. The first measure is the traditional sample correlation. Simply put, it is the covariance between the returns on a country/industry index and the world market index, divided by the product of standard deviations of both indexes. More specifically,

$$\rho_{iG,sample} = \sigma_{iG}/(\sigma_i \sigma_G) \tag{1}$$

where $\rho_{iG,sample}$ (σ_{iG}) indicates the correlation coefficient (covariance) between returns on local industry/country i and the global market index G, σ_i (σ_G) denotes the standard deviation of returns on local industry/country (the global market index). Sample correlation is calculated for each industry/country index, as well as for each month in the research period using daily returns within a month.

The second correlation measure is the implied correlation from a factor model. Under the assumption of an N-factor model, Bekaert et al. (2009) show that covariance between two asset returns is equal to

$$cov(R_{it}, R_{jt}) = \beta'_{it} V_t \beta_{jt} + cov(\varepsilon_{it}, \varepsilon_{jt}) \tag{2}$$

where β_i (β_j) is an Nx1 vector of factor loadings for asset i (j), V is an NxN matrix of factor covariances, and ε_i is the residual term from the factor model. Hence, the sample covariance is the summation of two covariance terms. Bekaert et al. (2009) name the first term on the right-hand side of Eqn. (2) as the model-implied covariance and the latter term as the idiosyncratic covariance. Model-implied correlation is computed by dividing the model-implied covariance term by the product of standard deviations of asset returns. As the model-implied correlation depends on systematic factor loadings, it can be considered as a systematic correlation.

We use the global version of the Fama and French (1993) three-factor (FF3) model as a benchmark global asset-pricing model, which is shown in Eqn. (3):

$$R_{it} = \alpha_i + \beta_{i1} R_{G_t} + \beta_{i2} SMB_t + \beta_{i3} HML_t + \varepsilon_{it} \tag{3}$$

where R_{it} indicates the daily excess return on local industry/country i on day t, α_i is the Jensen alpha. The three international factors are taken from the Kenneth French Data Library and they are defined as follows. R_{G_t} is the daily excess return on the value-weighted portfolio of stocks from developed markets. In calculating the excess returns, U.S. one-month T-Bill rate is used as the risk-free rate. SMB_t and HML_t are obtained from 2x3 independent sorts on size and B/M, which produces three big (small) stock portfolios with different levels of B/M, and two high (low) B/M portfolios with different levels of size. SMB_t is the equal-weighted average of the returns on the three small stock portfolios minus the average of the returns on the three big stock portfolios. HML_t is the equal-weighted average of the returns for the two high B/M portfolios minus the average of the returns for the two low B/M portfolios.[2] Eqn. (3) is estimated for each month in the research period using daily returns within a month, thus, beta estimates are obtained every month and are—therefore—allowed to vary.

Next, we express covariance between the return on a local industry/country (R_{it}) and the return on the global market (R_{gt}) by using the representation of R_{it} in Eqn. (3).

$$cov\,(R_{it}, R_{G_t}) = cov\,(\alpha_i + \beta_{i1}R_{G_t} + \beta_{i2}SMB_t + \beta_{i3}HML_t + \varepsilon_{it}, R_{G_t}) \tag{4}$$

Using the properties of the covariance operator, Eqn. (4) can be rearranged as follows:

$$cov(R_{it}, R_{G_t}) = cov(\alpha_i, R_{G_t}) + cov(\beta_{i1}R_{G_t}, R_{G_t}) + cov\,(\beta_{i2}SMB_t, R_{G_t}) + cov(\beta_{i3}HML_t, R_{G_t}) + cov(\varepsilon_{it}, R_{G_t}) \tag{5}$$

The first and the last terms in the right-hand side of Eqn. (5) are equal to zero. $cov(\alpha_i, R_{G_t})$ is zero, as the covariation of a constant with a variable is zero. $cov(\varepsilon_{it}, R_{G_t})$ is also zero because of the assumption of regression analysis that error terms and independent variables are orthogonal. These simplifications, as well as further rearrangement, yield Eqn. (6):

$$\sigma_{iG,implied} = \beta_{i1}cov(R_{G_t}, R_{G_t}) + \beta_{i2}cov\,(SMB_t, R_{G_t}) + \beta_{i3}cov(HML_t, R_{G_t}) \tag{6}$$

Using Eqns. (1) and (6), the return correlation between industry/country index i and the global market index G can be expressed as follows:

$$\rho_{iG,implied} = \beta_{i1}\,\sigma_G/\sigma_i + \beta_{i2}cov\,(SMB_t, R_{G_t})/\sigma_i\sigma_G + \beta_{i3}cov(HML_t, R_{G_t})/\sigma_i\sigma_G \tag{7}$$

where $\rho_{iG,implied}$ indicates the correlation coefficient implied from the FF3 model and is called the implied correlation. σ_i is the standard deviation of returns on local industry/country i. Finally, σ_G is the standard deviation of returns on the global market index.

3.3. Basic Statistics

Figure 2 depicts the time-series behavior of the sample correlation's cross-sectional mean across industry and country indexes. In addition, Figure 3 demonstrates the evolution of the cross-sectional mean of implied correlation. One of the notable points in the figures is that neither industry nor country indexes are perfectly integrated with the world market because average correlations are not close to one for both correlation measures. These indexes are also not fully segmented, as the average correlations are not zero as well. Hence, both groups of

[2] Please see http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html for further details.

indexes are partially segmented/integrated. Another interesting result is that local industries have lower average correlations than countries, again, for both types of correlation measures. The mean difference test results, which are not tabulated, show that time-series averages of mean cross-sectional sample correlation are 0.3256 and 0.4129 for industry and country indexes, respectively. Additionally, the difference between the means is highly significant at the 1% level. Similarly, average implied correlations for industry and country indexes, which are 0.2912 and 0.3692 respectively, significantly differ from each other at the 1% level.

< Insert Figure 2 here >

< Insert Figure 3 here >

Next, we have a closer look at the coefficient of variation ratios which is defined as the ratio of cross-sectional standard deviation to cross-sectional means of correlation measures. This ratio provides more insights about comparing the variability of correlation measures relative to their means for the two different samples. The time-series averages of the cross-sectional coefficient of variation ratios of both industry and country indexes for the sample (implied) correlation, which are not tabulated, are 0.84 (0.91) and 0.69 (0.76), respectively. This means that industry indexes exhibit more cross-sectional variability, with respect to the mean for both correlation measures. As a result, they have heterogeneous degrees of segmentation. Oppositely, country indexes demonstrate less cross-sectional variation and more uniformity in correlation measures. This is indicative of a relatively homogenous degree of integration across countries. These preliminary analyses show that local industries have more potential for international diversification for at least two reasons. First, they have lower correlations with the world market index—on average—as compared to country indexes. Second, there is a large cross-sectional variation in correlation measures across industry indexes, as opposed to country indexes. So, having a more efficient investment opportunity set for industry indexes is more likely.

< Insert Table 1 here >

Some descriptive statistics for the variables used in the study are shown in Table 1. Two panels of the table provide information for industry and country indexes, separately. In order to find the values reported in the table, we first calculate the cross-sectional means of variables across industries or countries for each month. Then, we use the time-series data for cross-sectional means to compute the mean, median, and standard deviation.

< Insert Table 2 here >

Time-series correlations between the cross-sectional means of variables are presented in Table 2. No substantial correlations are detected between variables, except the one between the sample correlation and implied correlation. As these correlation measures are alternative to each other, a high correlation between them is not surprising. These variables will not be included in the same regression specifications; therefore, we expect no potential econometric problems such as multi-collinearity.

4. Methodology

Firstly, portfolio sorts are used to examine the potential cross-sectional relationship between correlation measures and future index returns, which has implications for the international diversification policy. Then, the cross-sectional regressions are run to examine the same relationship after controlling for a set of control variables.

4.1. Portfolio Sorts

In portfolio sorts, we rank indexes based on their sample or implied correlations into quintile portfolios for each month. We calculate equal- and value-weighted returns on these correlation portfolios over the next month. Then, we examine whether there is a risk-adjusted return difference between portfolios with the lowest and highest correlation measures. To achieve this, we regress the raw return difference between the low- and high-correlation portfolios on some risk factors to isolate any systematic effects on returns. Any return pattern that remains after risk adjustment can be attributed to the cross-sectional relation between future index returns and correlation measures. A risk-adjusted return difference; or in other words, a significant Jensen alpha; has a special meaning in the context of partial market segmentation/integration theories when risk adjustment for a locally priced asset is based on global factors.

To explain the international diversification implications of a significant alpha from a global risk model, we revisit the partial market segmentation/integration theories. In integrated markets, assets that are in the same risk group provide the same expected returns because the same global systematic risk factors govern returns. In contrast, assets with comparable levels of risk in segmented markets can earn considerably different expected returns as local factors, which are specific to a local market, drive asset returns. Many of the emerging markets are neither fully integrated nor fully segmented. Rather, they exhibit a partially segmented/integrated nature. Theoretical contributions accommodating the partial segmentation/integration in asset pricing by Errunza and Losq (1985), Eun and Janakiramanan (1986), Alexander et al. (1987), and de Jong and de Roon (2005) show that when markets are on their way in switching from a segmented state to an integrated state, expected returns (or cost of equity capital) decrease because of a higher degree of risk-sharing between local and international investors. Many other studies provide empirical evidence in favor of a reduction in expected returns associated with market integration (Bekaert & Harvey, 2000; Errunza & Miller, 2000; Henry, 2000; Chari & Henry, 2004). In these studies, the main reasoning for lower expected returns in integrated markets rests on the following argument. Expected market returns are determined by the variance of return on the local market in a segmented market, whereas they are associated with the covariance between local and world market returns in an integrated market. Given the high return volatility in local markets (Harvey, 1995; De Santis & Imrohoroglu, 1997), the return variance of a local market is generally higher than the covariance between the local and global market returns. Consequently, an index representing a segmented market, or an industry delivers a higher expected return than its integrated counterpart.

This result has important implications to determine the segmented indexes using global asset pricing models. A locally priced segmented index will yield a positive alpha relative to a global asset pricing model. This is because a global factor model will command a lower expected return on this asset. On the other hand, no significant alpha is anticipated in the regression of integrated index returns on global risk factors in a correctly specified global risk model. If our conjecture is true, a trading strategy that goes long segmented indexes (characterized by low return correlations with the world market) and shorts integrated indexes (identified by high correlations) should produce a positive alpha in a universe of heterogeneously segmented international assets. This implies a negative cross-sectional relation between correlation and future index returns. However, if there are no segmented indexes in an international asset universe, then there will be no mispricing in a global setting. Accordingly, a trading strategy based on correlation will generate no significant alphas and thus will indicate no relation between correlation and future returns in a sample of integrated indexes.

A long-short trading strategy may also not yield a significant alpha if there is not a notable cross-sectional variation in correlation measures across portfolios. In such a case, the top and bottom portfolios have similar levels of correlation. Some extent of heterogeneity in correlation across tradable portfolios is required to be able to examine a cross-sectional relation between correlation and expected returns. Otherwise, portfolios contain assets that are almost randomly distributed and leave no return pattern that can be attributed to changes in correlation because correlation does not vary at all across portfolios. Any uniformity (variation) in correlation across portfolios is an indication of homogeneity (heterogeneity) in the degree of segmentation/integration of indexes from alternative samples. The existence of heterogeneously segmented indexes (i.e., indexes with varying levels of low correlation) in a sample implies a negative correlation-return relation and improves the international diversification potential of that sample.

In summary, examining the existence of positive alphas from global factor models in alternative asset universes of countries and industries allows for an indirect way of determining which set of assets contains segmented or heterogeneously segmented indexes. Hence, this approach enables us to find out the asset universe with a higher potential for international diversification. To our best knowledge, this is the first study that uses significantly positive Jensen alphas from global asset pricing models to detect whether there are heterogeneously segmented indexes in alternative asset universes that will improve international diversification.

In estimating alphas, we employ two different global factor models. The first model is the global FF3 model, as stated in Eq. (8); the second one is the global version of the Fama and French (2015) five-factor model and is extended by the momentum factor of Carhart (1997), which is called the FFC6 model and expressed in Eq. (9) below:

$$R_{l-h,t} = \alpha_{FF3} + \beta_1 R_{G,t} + \beta_2 R_{SMB,t} + \beta_3 R_{HML,t} + \varepsilon_t \quad (8)$$

$$R_{l-h,t} = \alpha_{FFC6} + \beta_1 R_{G,t} + \beta_2 R_{SMB,t} + \beta_3 R_{HML,t} + \beta_4 R_{OP,t} + \beta_5 R_{INV,t} + \beta_6 R_{MOM,t} + \varepsilon_t \quad (9)$$

where $R_{l\text{-}h,t}$ is the return difference between the low- and high-correlation quintiles in month t. The factors in Eq. (8) and Eq. (9) are obtained from Kenneth French's Data Library and how the factors in Eq. (8) are constructed is explained before when the factors in Eq. (3) were defined. Returns on *OP* and *INV* factors are calculated from the 2x3 independent sorts on market capitalization and one of the characteristics of operating profitability or investment at the end of each June. Two size portfolios (big and small) are formed based on market-capitalization sorts. The big portfolio contains the assets in the top 90% of market capitalization, whereas the small portfolio contains those in the bottom 10%. For operating profitability and investment, 30th and 70th percentiles are used to form three portfolios. The intersection of two size portfolios with three operating profitability portfolios (high, neutral, and low) will result in three big and three small portfolios with varying levels of profitability. This procedure is repeated for investment. Return on *OP* (*INV*) is the return difference between the average return on the two robust profitability (conservative investment) portfolios of big and small size and the average return on the two weak profitability (aggressive investment) portfolios of big and small size. Last, the return on the *MOM* factor of Carhart (1997) is similarly calculated from 2x3 sorts on size and momentum; it is the average return for the big and small winner portfolios minus the average of the returns for the big and small loser portfolios. Momentum is defined as the cumulative return from month t–12 to month t–2. α_{FF3} (α_{FFC6}) is the Jensen alpha from the global version of the FF3 (FFC6) model, as represented in Eq. (8) (Eq. (9)). A positive significant alpha will indicate that partially segmented portfolios that have low correlations earn higher risk-adjusted returns than partially integrated portfolios with high correlations. This signifies a negative cross-sectional relation between correlation and future index returns.

4.2. Cross-sectional Regressions

Another method for testing the existence of a relationship between correlation and future index returns is to run cross-sectional regressions. In contrast to portfolio sorting methodology, regression analysis allows for including an extensive array of control variables, while examining a cross-sectional relationship between two variables. Benefiting from this advantage of regression analysis, we examine the relationship between future index returns and correlation measures after controlling for widely reported return predictors in the literature such as *EBITDA/EV*, size, return on equity, earnings-to-price ratio, operating profitability, investment, momentum, and idiosyncratic volatility. More technically, we run the following cross-sectional regression specification for each month in the research period.

$$R_{i,t+1} = \gamma_0 + \gamma_1 CORR_{i,t} + \gamma_2 EBITDA/EV_{i,t} + \gamma_3 MV_{i,t} + \gamma_4 ROE_{i,t} + \gamma_5 EP_{i,t} + \gamma_6 OP_{i,t} + \gamma_7 INV_{i,t} + \gamma_8 NSI_{i,t} + \gamma_9 MOM_{i,t} + \gamma_{10} IVOL_{i,t} + \varepsilon_{i,t+1} \quad (10)$$

where $R_{i,t+1}$ one-month ahead return on index i, *CORR* is one of the two correlation measures (either the sample correlation or implied correlation) that are calculated in month t. Only one of the correlation measures is included in each regression specification. All control variables, which were previously defined in Subsection 3.2., are measured at month t. Eq. (10) is estimated monthly across industry and country indexes separately; additionally, the monthly estimates of regression parameters are stored. Then, the time-series averages of parameter estimates, including slope coefficients, are calculated to test whether these averages deviate from zero. Following Newey and West (1987), t-statistics of the average slope coefficients as well as the intercept term are adjusted for both heteroscedasticity and autocorrelation.

5. Results

5.1. Univariate Portfolio Sorts

We start our analyses by sorting indexes based on two correlation measures into quintile portfolios for each month. Quintile 1 (5), named *Corr*1 (*Corr*5), contains indexes with the lowest (highest) return correlation with the global market portfolio. The *Corr*1-5 portfolio is the long-short portfolio that goes long the quintile of *Corr1* and shorts *Corr5*. Then, we calculate the next month's equal- and value-weighted portfolio returns. In calculating the value-weighted returns in month t+1, we use the market capitalizations in month t. Thus, we obtain a monthly time series for the quintile returns. The time-series averages of quintile returns, as well as those of the long-short portfolios, are reported in Table 3. Moreover, we also report the alphas on the *Corr*1-5 portfolio from the FF3 and FFC6 models.

< Insert Table 3 here >

In Panel A of Table 3, where the results of equal-weighted portfolios are presented, the average raw returns on *Corr*1-5 are significantly different from zero for the sample of industries for both measures of correlation. For the sample correlation, the average raw return on the long-short portfolio is 0.67% per month with a Newey and West (1987) adjusted t-statistic of 3.52; meanwhile, it is 0.75% with a t-statistic of 3.25 for the implied correlation. When the raw returns are adjusted for risk with respect to the FF3 and FFC6 models, we still observe significant alphas. For instance, alphas from the FFC6 model are 0.89% and 0.76% for the sample correlation and implied correlation, respectively. These results show that industry indexes that are weakly correlated with the global market earn higher average returns than indexes with a strong correlation. In other words, the lower the correlation, the higher the return (and vice versa). Thus, univariate portfolio sorts on correlation measures indicate a negative relation between correlation and future returns for industries. However, such a relationship does not hold for country indexes. We report no significant raw returns or alphas on the long-short portfolio for any of the two correlation measures for country indexes.

Low-correlation industry indexes are likely to be partially segmented from the global market. Partially segmented indexes are more dominantly priced by local factors and do not achieve a high degree of risk-sharing with international investors. As a result, these indexes are riskier than integrated indexes and provide a higher expected return than that is commanded by an asset-pricing model that only includes global factors. This gives rise to positive alphas.

Therefore, it is expected that industry indexes with positive alphas from global asset-pricing models are either segmented or partially segmented from the global market.

Inversely, we find that country indexes that are sorted on correlation do not generate significant alphas. There are two potential reasons for this result. First, country indexes can have a higher degree of integration with the world market. This makes global factors more important in the pricing of country indexes. Accordingly, global asset-pricing models better explain country returns, leaving no alpha in returns of country indexes. The second reason is that countries reach a homogenous degree of market integration during the globalization process, as evidenced by lower coefficients of variation for correlation measures that were previously documented. This can explain why both low- and high-correlation country quintiles do not exhibit cross-sectional variation in correlation measures. Therefore, any change in return on the long-short correlation portfolio for country indexes cannot be linked to the difference in correlation between top and bottom portfolios, as there is no substantial difference.

It is also worth mentioning that value-weighted *Corr*1-5 industry portfolios, presented in Panel B of Table 3, do not deliver abnormal returns. None of the raw or risk-adjusted returns are significantly different from zero. Hence, the results obtained for the industries in Panel A seem to be specific to small industry indexes; this can be due to equal-weighted portfolios being overrepresented by small indexes, whereas value-weighted portfolios are dominated by large indexes. To test this hypothesis, we conduct dependent bivariate sorts based on size and correlation.

5.2. Bivariate Portfolio Sorts

First, we sort industry indexes based on market capitalization into quintile portfolios. Then, we further sort industry indexes based on correlation within each size quintile into quintiles to obtain 5x5 size-correlation portfolios. Finally, we calculate the average returns on size-correlation portfolios, as well as *Corr*1-5 portfolios within each size quintile. In addition, we estimate the alphas on *Corr*1-5 portfolios and report the results in Table 4. The *MV*1 quintile contains the industry indexes with the smallest market capitalizations, whereas *MV*5 contains the biggest indexes. Indeed, both the economic and statistical significance of abnormal returns for the long-short correlation portfolio are the highest within the smallest size quintile of *MV*1. The FFC6 alphas are 2.06% with a t-statistic of 4.27 and 1.64% with a t-statistic of 3.32 for the sample and implied correlations, respectively. As the size of the quintiles increases, the alphas and t-statistics diminish, though not monotonically. For the *MV*5 size quintile, the alphas on *Corr*1-5 drop to 0.5% (t-stat=1.88) and 0.31% (t-stat=1.33). These results for industry indexes support the results seen in Table 3. The abnormal profit opportunities based on correlation sorts are only existent or stronger in the small industry indexes.

These results are consistent with partial market segmentation/integration theories of international finance. Small indexes, i.e., indexes with lower market capitalization; are generally progressing towards maturity and becoming integrated with the global markets. International investors typically invest in large and liquid local assets while ignoring small ones (Dahlquist & Robertsson, 2001; Christoffersen et al., 2006). This disrupts risk sharing in the pricing of local small assets and keeps them segmented. Thus, the higher positive alphas on small industry indexes, which are expected to be segmented, are in line with the implications of the partial market segmentation/integration theories.

< Insert Table 4 here >

Furthermore, we conduct bivariate sorts on size and correlation for country indexes. Rather than conducting 5x5 sorts, we perform 3x2 sorts in order to not to have too few indexes in portfolios, as the number of country indexes is substantially smaller than the number of industry indexes. The results in Table 5 demonstrate that neither the raw nor the risk-adjusted returns on the long-short correlation portfolios within any of three size portfolios significantly depart from zero at the 5% significance level. In other words, a trading strategy that goes long country indexes with the lowest correlations and shorts those with the highest correlations is incapable of creating abnormal returns, regardless of the size of country indexes. This finding is, again, in conformity with the results in Table 3 where it is shown that the trading strategy based on correlation measures does not provide profit opportunities for both equal- and value-weighted portfolios of country indexes.

< Insert Table 5 here >

5.3 Cross-Sectional Regressions

Having shown that industry indexes with low correlation earn higher abnormal returns, our next aim is to examine whether this negative relationship is robust to the inclusion of control variables. Because portfolio sorting methodology is not suitable for including many control variables simultaneously, we conduct cross-sectional regressions to accommodate a set of variables controlling for size, value, momentum, profitability, investment, net share issuance, and idiosyncratic volatility effects. The time-series averages of regression coefficients, as well as Newey and West's (1987) t-statistics, are reported in Table 6. Panel A of the table presents the results for industry indexes. Regression analyses confirm the negative cross-sectional relation between correlation and industry returns. The slope coefficient on sample correlation is -0.0056, with a t-statistic of -2.01. Implied correlation is also negatively related to industry returns, albeit this relationship is insignificant. The control variables that have significant slope estimates are *EBITDA/EV*, *MV*, *EP*, *OP*, *INV*, *MOM*, and *IVOL*. Hence, the relationship between sample correlation and industry returns remains strong, even after controlling for so many different effects. The results for the countries presented in Panel B indicate that neither of the correlation measures departs from zero, as evidenced by the insignificant t-statistics of -1.41 and -1.22 for the sample and implied correlations, respectively. These findings for the countries support the findings of portfolio sorts in Tables 3 and 5, which also fail to provide evidence in favor of a relation between correlation measures and country returns.

< Insert Table 6 here >

The results from portfolio sorts and cross-sectional regressions obtained, so far, confirm each other and indicate that there is a negative relation between the correlation and future industry returns. However, no relation between correlation and future country returns has been recorded. Investing across industries that have low correlations with the global market provides more profit opportunities than investing across countries. A plausible explanation for both the profitability of investing across industries and the non-profitability of investing across countries is that industry indexes (especially the ones with low correlation) are less integrated than country indexes. Using a novel segmentation measure, Bekaert et al. (2011) show that, indeed, there is a large heterogeneity among industries across countries in their degree of segmentation because some of the countries may have a comparative advantage in certain industries due to their local resources, conditions, or geographic location. Accordingly, certain industries can become more integrated and developed in some countries, while remaining segmented and emerging in some other countries. Segmented industries across countries can extend the opportunity set of international investors and provide a better risk-return tradeoff. On the contrary, the differences in countries (in the extent of their segmentation) are expected to diminish, as the globalization process may lead country correlations to converge. Another reason for the narrowing gap in country correlations is that the differences in industries are diversified away in country indexes that consist of several industry indexes. Therefore, country indexes may not serve as an ideal alternative asset universe that enhances international diversification. In summary, an international diversification strategy that prioritizes industry allocation is superior to a strategy that puts more emphasis on country allocation.

5.4. Sub-period Analyses

Finally, we revisit the discussion of whether the benefits of international diversification evaporate when they are most needed (i.e., during turbulent times). Longin and Solnik (2001) and Brooks and Del Negro (2004) show that stock-market correlations substantially increase during down markets or crisis periods. The association between high-correlation periods and turbulent times is also documented by Qian et al. (2020) in crypto currency markets and by Zaremba et al. (2021) in commodity markets. To examine this issue, we split the full sample into high- and low-volatility months. This classification is based on the monthly volatility of the world market index. For each month in the research period, we calculate the monthly standard deviation of the world market index using daily returns within a month. Then, we calculate the median of monthly standard deviations. If the standard deviation in a month is above the median, then that month is classified as a high-volatility month. Otherwise, it is classified as a low-volatility month. Regressions are run separately for high- and low-volatility months and the results are shown below in Table 7.

< Insert Table 7 here >

For industry indexes, both sample correlation and implied correlation have negatively significant slopes of -0.0112 (t-stat=-1.95) and -0.0120 (t-stat=-2.17) respectively during high volatility months, as can be seen in Panel A. So, in contrast to the common view that international diversification benefits disappear during instable periods, these results demonstrate that international diversification through investing in segmented industry indexes with low correlations still yields positive returns in the next period; thus, providing profit opportunities for global investors. These results are intuitive in the sense that the effects of negative global shocks will not be transmitted or be partially transmitted to segmented industries that can be seen as safe havens during large global market falls. Local pricing of segmented industries can keep the effects of global shocks away from international portfolios that contain segmented industries.

During stable periods, the sign of the relationship between correlations and returns switches to positive. However, this relationship is not as strong as the one detected in high-volatility months. While the slope of the implied correlation has a positive significant slope of 0.0051 with a t-statistic of 1.72, that of sample correlation is positive but insignificant in Panel B. Nevertheless, global investors can also benefit from this weak positive correlation. Stable periods are generally characterized by expansionary movements in the overall economic activity, as well as by positive global market returns. Integrated industry indexes with high correlations with the global market earn positive future returns when global market return undergoes a rise due to the positive link detected in low-volatility periods. In sum, cross-industry diversification can be translated into profit opportunities through different channels depending on the stability of markets. Having segmented industry indexes in a global portfolio during turbulent times and integrated industry indexes during tranquil times will improve future returns.

The results for country indexes in Panels C and D indicate no relationship between country correlations and country returns, regardless of whether the markets are volatile or not. The results from sub-period analyses consistently support the results from the full sample and verify that there is no association between country correlations and returns. Overall, the main message from sub-period analyses is that investing across industries rather than countries as a part of the international diversification strategy can improve returns not only in tranquil but also in stable periods.

5.5. Robustness Tests

5.5.1. Emerging vs Developed Markets

Our finding of a negative relationship between index correlations and future industry returns in the presence of segmented industries suggests that this relationship can be stronger for a subsample of industries, which is expected to include more segmented industries. A more segmented subsample can be obtained by grouping the sample based on the development stage of markets. Emerging markets are a natural host for segmented industries. Some industries may not advance in emerging markets either due to a lack of natural resources, technology, and knowledge or to local barriers against foreign investor participation in some strategic sectors (such as defense and telecommunications). As a result, some sectors in emerging markets may stay local and segmented. If this is the case, then the negative relation between correlation and index returns should be stronger or only exist in emerging markets where segmented industries cluster.

To test this conjecture, we divide the sample into emerging and developed markets and rerun the cross-sectional regression analysis. The results presented in Panel A of Table 8 indicate that, indeed, the negative relation between correlation and future industry returns only exists for industry indexes from emerging markets. Both slope estimates for correlation measures (-0.0109 and -0.0075) are distinguishable from zero at a 5% significance level. The results for industry indexes from developed markets in Panel B show no significant slopes for any of the correlation measures, although they are all negative. The main inference from these results is that the negative relation detected for the full industry sample is driven by the subsample of industries from emerging markets. This result conforms with our expectations that there are segmented industries in emerging markets that can cause this negative relation. In summary, we show that the negative association between index correlation and industry returns is more prominent for segmented industries that are concentrated in emerging markets.

< Insert Table 8 here >

The results for developed and emerging country indexes are presented in Panels C and D of Table 8. Before discussing the subsample results of country indexes, remember that the full sample results that were presented earlier indicated no association between correlation and country index returns. This means that either there are no substantially segmented indexes in the universe of country indexes or the variation in the degree of segmentation across countries is negligible, as the negative relation arises in the presence of heterogeneously segmented indexes according to our conjecture. If there were even a few segmented indexes or indexes with different degrees of segmentation in country subsamples, they would be captured by the low-correlation portfolio and manifest their effects in the full sample by inducing a negative relationship between correlation and returns. Because we fail to find evidence for a negative relationship in the full sample, we conclude that country indexes are both homogeneously and partially integrated. The homogeneity of integration across countries makes it likely that any subsample of country indexes will show a similar degree of integration to that of the full sample. Therefore, it is not expected to observe a significant correlation-return relationship in the subsamples as well. The results in Panels C and D confirm our expectations and indicate insignificant slope estimates for correlation measures.

5.5.2. Segmented vs Integrated Markets

So far, we assumed that segmented (integrated) indexes are loosely (strongly) correlated with the global market and that some indexes from emerging markets can exhibit a segmented character. Now, we classify indexes as either segmented or integrated based on the segmentation measure of Bekaert et al. (2011), which is independent of correlations or the development stage of markets. We examine whether this alternative segmentation/integration classification produces similar results to the ones that were obtained in previous parts.

The classification approach of Bekaert et al. (2011) has the ability to group industries (countries) as segmented/integrated industries (countries), depending on the comparison of earnings yields (*EY*) of individual indexes to that of the relevant global industry index (the world market index). The intuition behind this approach for the industry classification rests on the following idea. *EY* of an individual segmented (integrated) industry in a country should be different from (similar to) *EY* of the relevant global industry because the profitability (or earnings) in an industry is determined by different (common) local (global) factors. The deviation of a local industry's *EY* from the *EY* of the global industry represents the degree of segmentation of that industry in a particular country. In other words, the higher the difference between the *EY* of a local industry index and that of a global industry index, the higher the segmentation of that local industry. Then, the degree of segmentation (*SEG*) for a certain global industry is calculated as the average of the absolute value of *EY* differentials for the same industry across countries.

More specifically, we calculate *SEG* for each of the 19 global industry indexes as follows:

$$SEG_{jt} = \sum_{i=1}^{N} IW_{ijt} \left| EY_{ijt} - EY_{wjt} \right| \tag{11}$$

where SEG_{jt} indicates the degree of segmentation for global industry j in month t; IW_{ijt} shows the weight of local industry j belonging to country i in the global industry index; EY_{ijt} is the earnings yield of local industry j in country i, which is the reciprocal of price-earnings ratio; and EY_{wjt} is the earnings yield of global industry j. i changes from 1 to 63 for 63 countries and j changes from 1 to 19 for the 19 global industries. Monthly price-earnings ratios for each industry across all countries are obtained from Datastream to calculate the monthly *SEG* variable. Equal weights are used in the calculation of average absolute *EY* differentials. Under full industrial integration, the *SEG* value of a global industry (SEG_{jt}) is expected to converge to zero, as the local and global values of *EY* (EY_{ijt} and EY_{wjt}, respectively) are close to each other. Median values of *SEG* are calculated for the 19 global industries for each month in the research period. Then, local industries that have *SEG* values greater than the median *SEG* of the relevant global industry are placed into the segmented industry subsample. Conversely, industries with below-median *SEG* values are used to form the integrated industry subsample.

Finally, the cross-sectional regressions are estimated for these subsamples and the results are presented in the top two panels of Table 9. Highly significant slope estimates of -0.0077 (t-stat=-2.52) for the sample correlation and -0.0060 (t-stat=-1.98) for the implied correlation are reported in Panel A, which shows the results for the segmented industry subsample. On the contrary, the results for the integrated industry subsample shown in Panel B demonstrate no significant slope estimates for both correlation measures at a 5% significance level. Nevertheless, the slope estimates on correlation measures are still negative.

< Insert Table 9 here >

To construct *SEG* variables for countries, similar arguments are employed as explained above. A country index is assumed to be a value-weighted portfolio of industries that exist in a country. The country-specific *SEG* variable is defined as the weighted average of industry differentials. *SEG* is calculated monthly for all 63 countries. Countries with above-median *SEG* values form the segmented country subsample for that month, and the integrated country subsample is composed of the remaining countries. The results for the cross-sectional regressions for the subsamples of segmented and integrated countries are provided in Panels C and D of Table 9. Neither for the segmented nor the integrated country subsamples, is a significant relation between correlation and country returns found. Therefore, correlation is not a return predictor in the cross-section of country indexes and does not play a role in improving the profits of country portfolios. This restricts the diversification potential of investing across country indexes.

The findings of a stronger negative relation between correlation and industry returns for segmented industries and of no relation between correlation and country returns in Table 9 are consistent with the findings of a negative relation between correlation and industry returns from emerging markets and of no link between correlation and country returns in Table 8. Both sets of findings suggest that there is a sizeable cross-sectional variation in correlations of industries that can affect future industry returns and that no relation between correlation and country returns is indicative of no remarkable cross-sectional variation in country correlations. Therefore, investing across local industry indexes, rather than country indexes, has more potential for international diversification.

6. Concluding Remarks

We test the conjecture that partially segmented (integrated) indexes characterized by low (high) correlation with the world market are mainly priced by local (global) factors and should produce positive (no) alpha relative to a global asset-pricing model. The idea behind this conjecture rests on the fact that risks, and thus expected returns, of assets in segmented markets are higher than those of similar assets in global markets, as there is no risk-sharing with international investors in segmented markets. Therefore, an expected return on a locally priced asset should be greater than the expected return that is estimated by a global asset-pricing model. This implies that if risk adjustment of a locally priced index is made with respect to global factors only, instead of local factors, then this practice should generate positive abnormal returns; i.e., alphas. Stated differently, positive alphas relative to global asset-pricing models can be used to detect segmented indexes that can improve the extent of international diversification. In order to deduce which sample of indexes provides much potential for efficient international diversification, we employ a trading strategy that goes long indexes with the lowest correlations with the world market and shorts the ones with the highest correlations. The sample that contains indexes with heterogeneous degrees of segmentation will generate top and bottom portfolios, differing significantly from each other in their degree of segmentation. Accordingly, the long-short portfolio based on correlation is expected to deliver a significant alpha, which is consistent with partial market segmentation/integration theories.

We show that the long-short correlation strategy provides positive alphas in a global asset-pricing model framework for the sample of industry indexes; however, it leaves no significant alphas for the sample of country indexes. These results indicate that the industry sample contains heterogeneously segmented indexes, whereas there is no evidence of a notable segmentation difference among country indexes.

We further show that average country correlations are higher than average industry correlations but are still less than one and exhibit relatively less variation across countries. This finding lends support to the view that country indexes are at a further stage on their way toward integrating with the global market. Although country indexes are not fully integrated with the global market, country correlations move in a narrower band, as compared to those of industry indexes. These results suggest that country indexes have a higher degree of integration than industry indexes and that the degree of integration is more uniform across countries. In other words, countries are partially integrated and have a homogeneous degree of integration. This can partly explain why sorting country indexes based on correlation does not lead to a risk-adjusted return difference between low- and high-correlation portfolios.

A positive alpha on returns of partially segmented indexes with lower correlations implies a negative relation between expected returns and correlations. Small market size, emerging country origin, and weak correlation with the global market are characteristics that are associated with locally priced assets. So, if the hypothesis that there is a negative relation between heterogeneously segmented index returns and correlations is true, then this negative relation should be more visible for the more segmented subsamples that are characterized by small market size and emerging country origin. The results from subsamples based on market size and development stage of markets confirm a stronger cross-sectional relationship. In addition, segmented/integrated index classification based on alternative segmentation measures that are apart from the correlation measure yields similar results. Finally, we showed that the international diversification potential of industries does not vanish during volatile periods when the benefits of international diversification are most needed. Hence, we conclude that industry diversification across countries is superior to mere country diversification and that it has the potential for more efficient international diversification.

Our results have important implications for portfolio managers. Equipped with the tool developed in this study to identify segmented indexes, global investors will achieve a more efficient diversification by including segmented indexes in their international portfolios. A more efficient diversification will allow to reduce the risk of the portfolio for a given level of expected return and increase the expected return for a given level of risk, and thus, improve the expected return per unit of risk.

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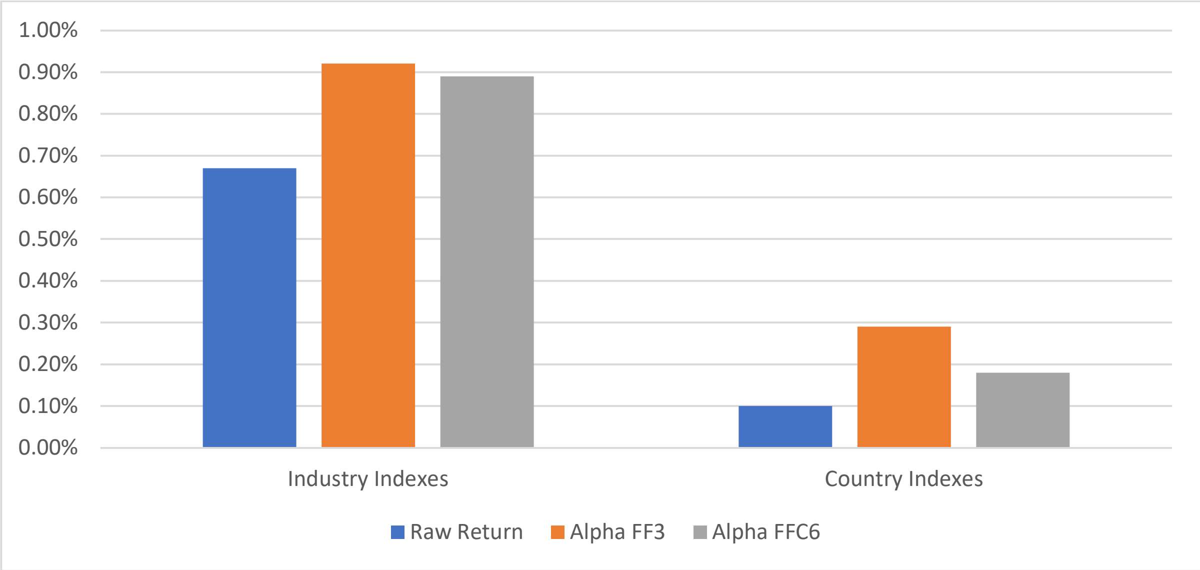

Figure 1: Performance of Long-short Correlation Portfolios

This figure depicts the returns on long-short correlation portfolios for industry and country indexes. Raw return, alpha from Fama and French (1993) three-factor model (Alpha FF3), and alpha from Fama and French (2015) five-factor model augmented by Carhart's (1997) momentum factor (Alpha FFC6) are used as the performance metrics. All raw returns and alphas are monthly and expressed in percentages.

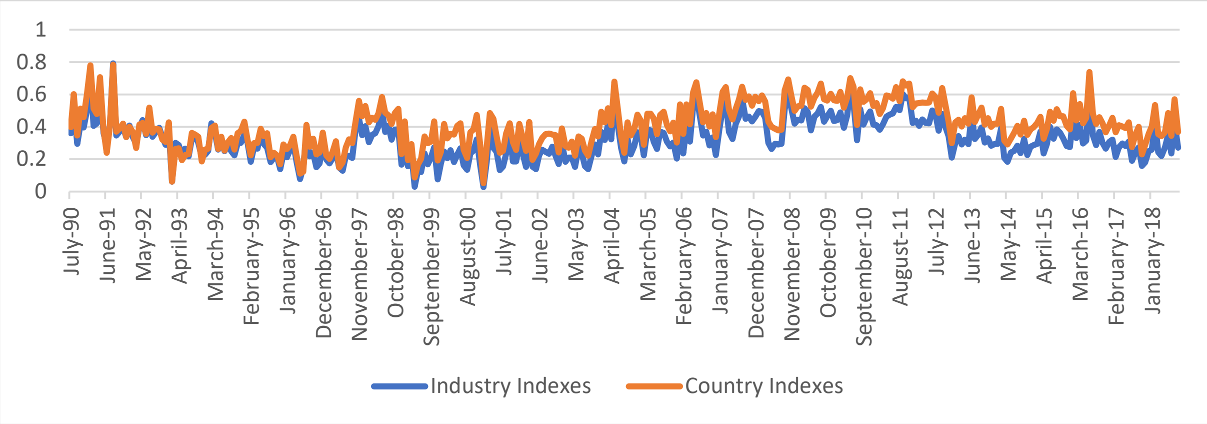

Figure 2. Mean Sample Correlations of Industry and Country Indexes
Figure 2 shows the cross-sectional means of the sample correlation across industry and country indexes through time.

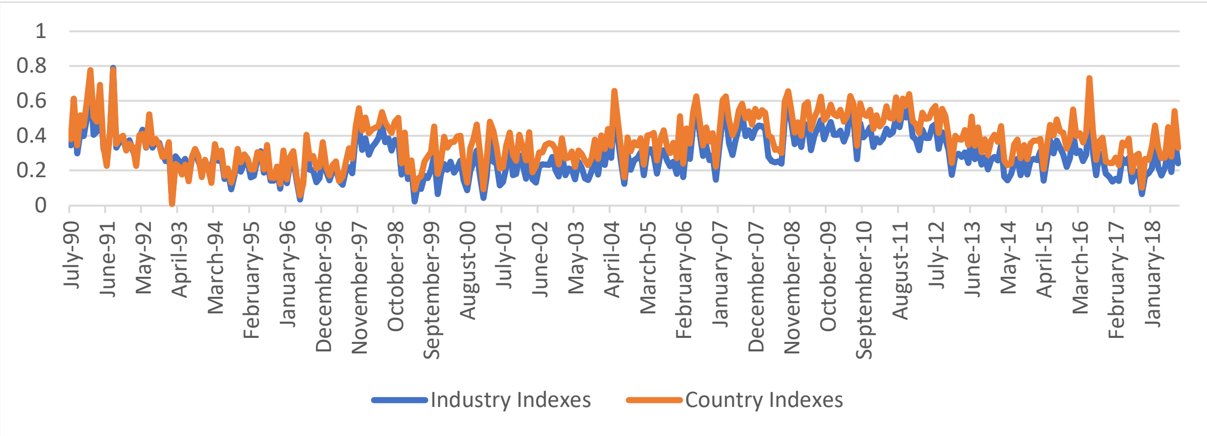

Figure 3. Mean Implied Correlations of Industry and Country Indexes
Figure 3 depicts the time-series evolution of the cross-sectional means of implied correlation across industry and country indexes.

Table 1. Descriptive Statistics for Industry and Country Indexes

Descriptive statistics for the variables are provided for industries (Panel A) and countries (Panel B), separately. To calculate the descriptive statistics, the cross-sectional means of the variables across industries or countries for each month are computed first. Then, monthly time-series data for cross-sectional means are used to calculate the mean, median, and standard deviation of variables. *Sample Corr.* is simply the covariance between the returns on an index and the world market index, divided by the product of standard deviations of both indexes. *Implied Corr.* is the correlation that is implied by the global version of the Fama and French (1993) three-factor model. *EBITDA/EV* indicates the ratio of earnings before interest taxes depreciation and amortization to enterprise value. *MV* is the market value of an index measured as the monthly market capitalization in billion dollars. *ROE* stands for the return on equity. *EP* shows the earnings-to-price ratio. *OP* is operating profitability. *INV* refers to investments. Net share issues (*NSI*) is the net change in shares outstanding. *MOM* denotes the momentum, calculated as the cumulative return over the last 12 months. Idiosyncratic volatility (*IVOL*) is the monthly residual volatility where residuals are obtained from the World CAPM, in which daily index returns are regressed on the return of the world market index.

	Panel A: Industries			Panel B: Countries		
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Sample Corr.	0.3256	0.3076	0.1195	0.4129	0.4087	0.1325
Implied Corr.	0.2912	0.2759	0.1198	0.3692	0.3618	0.1327
EBITDA/EV	0.4878	0.1325	1.4294	0.1187	0.1153	0.0469
MV	0.0490	0.0487	0.0113	0.5731	0.5654	0.2185
ROE	0.1401	0.1257	0.1892	0.1193	0.1106	0.0296
EP	0.0742	0.0714	0.0140	0.0750	0.0724	0.0135
OP	0.1765	0.1844	0.0816	0.1626	0.1622	0.0316
INV	0.2896	0.2806	0.1618	0.3840	0.2452	0.4549
NSI	0.0039	0.0029	0.0064	0.0045	0.0029	0.0081
MOM	0.1086	0.0998	0.1890	0.0793	0.0767	0.1880
IVOL	0.0690	0.0636	0.0177	0.0492	0.0453	0.0152

Table 2. Time-series Correlations between the Cross-sectional Means of Variables

For each month, cross-sectional means of the variables across industries or countries are computed first. Then, monthly time-series data for cross-sectional means are used to calculate the correlation between variables.

Panel A: Industry Indexes

	Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*
Sample Corr.	1.0000										
Implied Corr.	0.9593	1.0000									
EBITDA/EV	-0.0359	-0.0361	1.0000								
MV	0.2331	0.2528	-0.0376	1.0000							
ROE	-0.0133	-0.0126	0.0340	0.0072	1.0000						
EP	-0.0911	-0.0865	0.0926	-0.0884	0.0833	1.0000					
OP	-0.0020	-0.0019	0.0323	0.0249	0.2570	0.0526	1.0000				
INV	-0.0215	-0.0229	-0.0205	-0.0294	0.0053	0.0020	0.0254	1.0000			
NSI	0.0045	-0.0027	-0.0097	-0.0090	-0.0024	0.0010	-0.0072	0.0092	1.0000		
MOM	-0.0277	-0.0235	0.0186	-0.0074	0.0578	-0.0897	0.0149	-0.0026	0.0124	1.0000	
IVOL	-0.2357	-0.2297	0.0202	-0.1387	-0.0066	0.0868	-0.0028	0.0214	0.0104	0.0473	1.0000

Panel B: Country Indexes

	Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*
Sample Corr.	1.0000										
Implied Corr.	0.9664	1.0000									
EBITDA/EV	-0.1108	-0.1128	1.0000								
MV	0.2845	0.3131	-0.0792	1.0000							
ROE	-0.0852	-0.0799	0.0754	-0.0177	1.0000						
EP	-0.1629	-0.1555	0.1090	-0.1860	0.1189	1.0000					
OP	-0.0077	-0.0045	0.0615	0.0457	0.4234	-0.0280	1.0000				
INV	-0.1433	-0.1429	0.1201	-0.0638	0.0874	0.0445	0.0951	1.0000			
NSI	-0.0399	-0.0412	0.0271	-0.0337	0.0231	0.0091	-0.0130	0.0472	1.0000		
MOM	-0.0116	-0.0093	0.0680	-0.0096	0.1629	-0.1380	0.0373	-0.0352	0.0268	1.0000	
IVOL	-0.2819	-0.2841	0.1399	-0.1831	0.0169	0.1002	0.0296	0.0853	0.0309	0.0406	1.0000

Table 3. Univariate Portfolios Sorts on Correlation

Industry and country indexes are sorted into quintile portfolios based on the sample or implied correlation for each month. Then, returns on quintile portfolios are calculated over the next month. *Corr*1 quintile contains indexes that have the lowest correlations with the world market index, whereas *Corr*5 includes the ones with the highest correlations. *Corr*1-5 is the long-short portfolio that goes long the *Corr*1 portfolio and shorts the *Corr.* 5 portfolio. Time-series averages of returns on correlation portfolios are reported. Jensen alphas from Fama and French's (1993) three-factor model (Alpha FF3) and Fama and French's (2015) five-factor model, augmented with Carhart's (1997) momentum factor (Alpha FFC6), are also reported for the *Corr*1-5 portfolio. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panel A reports the returns on equal-weighted portfolios while Panel B reports those on value-weighted portfolios. Returns and alphas are reported in percentage terms. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Industries		*Countries*	
	Sample Corr.	*Implied Corr.*	*Sample Corr.*	*Implied Corr.*
Panel A: Equal-Weighted Portfolios				
*Corr*1	1.79	1.74	1.09	1.14
*Corr*2	1.39	1.34	1.21	0.87
*Corr*3	1.46	1.18	1.32	1.04
*Corr*4	1.23	1.28	1.07	0.87
*Corr*5	1.13	0.99	0.99	0.86
*Corr*1-5	0.67^{***}	0.75^{***}	0.10	0.29
	(3.52)	(3.25)	(0.44)	(0.91)
Alpha FF3	0.92^{***}	0.78^{***}	0.29	0.26
	(3.97)	(3.31)	(1.03)	(0.85)
Alpha FFC6	0.89^{***}	0.76^{***}	0.18	0.14
	(3.54)	(2.94)	(0.61)	(0.44)
Panel B: Value-Weighted Portfolios				
*Corr*1	1.05	1.26	0.79	0.77
*Corr*2	1.03	0.74	1.00	0.97
*Corr*3	1.02	0.88	1.07	0.75
*Corr*4	0.89	0.58	1.00	0.68
*Corr*5	1.05	0.80	0.87	0.77
*Corr*1-5	0.00	0.46	-0.08	-0.01
	(0.01)	(1.61)	(-0.30)	(-0.02)
Alpha FF3	0.24	0.33	-0.04	-0.11
	(0.91)	(1.19)	(-0.12)	(-0.33)
Alpha FFC6	0.28	0.25	0.18	-0.03
	(0.94)	(0.83)	(0.46)	(-0.06)

Table 4. Bivariate Portfolios Sorts on Size and Correlation for Industry Indexes

Industry indexes are first sorted based on market capitalization into quintile portfolios. Then, within each size quintile indexes are further sorted based on correlation into quintile portfolios to obtain 5x5 size-correlation portfolios. Average returns on size-correlation portfolios are calculated over the next month. *Corr*1 quintile contains indexes that have the lowest correlations with the world market index, whereas *Corr*5 includes the ones with the highest correlations. *MV*1 is the smallest size quintile and *MV*5 is the biggest one. *Corr*1-5 is the long-short portfolio that goes long the *Corr*1 portfolio and shorts the *Corr*5 portfolio. Time-series averages of returns on size-correlation portfolios are reported in the table. In addition, Jensen alphas from Fama and French's (1993) three-factor model (Alpha FF3) and Fama and French's (2015) five-factor model, augmented with the Carhart's (1997) momentum factor (Alpha FFC6), are also reported for the *Corr*1-5 portfolios within each size quintile. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panel A shows the results for sample correlation and Panel B presents the results for implied correlation. Returns and alphas are reported in percentage terms. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Sample Correlation						Panel B: Implied Correlation				
	*MV*1	*MV*2	*MV*3	*MV*4	*MV*5		*MV*1	*MV*2	*MV*3	*MV*4	*MV*5
*Corr*1	2.69	1.90	1.59	1.15	1.16		2.93	2.08	1.40	1.04	1.11
*Corr*2	2.78	1.57	1.37	1.05	1.10		2.60	1.44	1.15	0.95	0.71
*Corr*3	2.09	1.44	1.15	1.28	0.91		2.57	1.25	1.01	1.04	0.72
*Corr*4	2.33	1.24	1.07	1.08	1.05		2.63	1.19	0.95	0.87	0.81
*Corr*5	1.30	1.08	0.85	0.94	0.78		1.01	0.91	0.80	0.72	0.67
*Corr*1-5	1.38^{***}	0.83^{***}	0.74^{***}	0.20	0.37^{*}		1.91^{***}	1.18^{***}	0.60^{**}	0.32	0.44^{**}
	(3.79)	(3.62)	(3.73)	(1.02)	(1.80)		(4.00)	(4.52)	(2.54)	(1.47)	(2.01)
Alpha FF3	2.27^{***}	1.38^{***}	0.69^{***}	0.35	0.49^{**}		1.93^{***}	1.18^{***}	0.64^{***}	0.26	0.41^{*}
	(4.81)	(5.10)	(2.88)	(1.63)	(2.17)		(4.10)	(4.55)	(2.60)	(1.18)	(1.83)
Alpha FFC6	2.06^{***}	1.34^{***}	0.62^{**}	0.38	0.50^{*}		1.64^{***}	1.12^{***}	0.52^{*}	0.24	0.31
	(4.27)	(4.32)	(2.36)	(1.58)	(1.88)		(3.32)	(3.74)	(1.95)	(0.94)	(1.33)

Table 5. Bivariate Portfolios Sorts on Size and Correlation for Country Indexes

Country indexes are first sorted based on market capitalization into tertile portfolios. Then, within each size tertile, indexes are further sorted based on correlation into two portfolios to obtain 3x2 size-correlation portfolios. Average returns on size-correlation portfolios are calculated over the next month. *Corr*1 quintile contains indexes that have the lowest correlations with the world market index, whereas *Corr2* includes the ones with the highest correlations. *MV*1 is the smallest size quintile and *MV*3 is the biggest one. *Corr*1-2 is the long-short portfolio that goes long the *Corr*1 portfolio and shorts the *Corr2* portfolio. Time-series averages of returns on size-correlation portfolios are reported in the table. In addition, Jensen alphas from Fama and French's (1993) three-factor model (Alpha FF3) and Fama and French's (2015) five-factor model, augmented with the Carhart's (1997) momentum factor (Alpha FFC6), are also reported for the *Corr*1-2 portfolios within each size quintile. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panel A shows the results for sample correlation and Panel B presents the results for implied correlation. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

	Panel A: Sample Correlation			*Panel B: Implied Correlation*		
	*MV*1	*MV*2	*MV*3	*MV*1	*MV*2	*MV*3
*Corr*1	1.58	1.10	0.96	1.34	0.88	0.88
*Corr*2	1.18	1.15	0.87	1.06	0.86	0.72
*Corr*1-2	0.40*	-0.05	0.09	0.28	0.02	0.16
	(1.65)	(-0.26)	(0.64)	(1.21)	(0.11)	(1.11)
Alpha FF3	0.51*	-0.01	0.13	0.33	0.01	0.12
	(1.82)	(-0.06)	(0.91)	(1.44)	(0.04)	(0.71)
Alpha FFC6	0.55**	0.07	0.26*	0.52**	0.04	0.21
	(1.98)	(0.30)	(1.68)	(2.12)	(0.18)	(1.16)

Table 6. Fama-MacBeth Regressions

One-month ahead index returns are regressed on the sample or implied correlation, along with other control variables across indexes for each month in the research period. Time-series averages of monthly regression coefficients and R^2 values are reported in the table. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panel A shows the results for industry indexes while Panel B shows those for country indexes. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*	R^2
Panel A: Industry Indexes											
-0.0056**	-	0.0074***	0.0067**	-0.0008	0.0342***	0.0026*	-0.0011*	-0.0132	0.0109***	0.2019***	0.1501
(-2.01)	-	(2.58)	(2.08)	(-0.29)	(3.55)	(1.80)	(-1.85)	(-1.01)	(3.98)	(5.93)	
-	-0.0041	0.0074***	0.0064**	-0.0007	0.0343***	0.0028*	-0.0012*	-0.0127	0.0108***	0.2032***	0.1494
-	(-1.52)	(2.58)	(1.97)	(-0.28)	(3.57)	(1.91)	(-1.89)	(-0.98)	(3.88)	(6.00)	
Panel B: Country Indexes											
-0.0041	-	0.0381***	0.0003	0.0013	0.0480**	0.0033	-0.0032	0.0033	0.0142***	-0.0362	0.2999
(-1.41)	-	(3.10)	(0.83)	(0.10)	(2.21)	(0.37)	(-0.76)	(0.08)	(2.86)	(-0.76)	
-	-0.0033	0.0394***	0.0003	0.0017	0.0468**	0.0038	-0.0036	0.0072	0.0139***	-0.0318	0.2994
-	(-1.22)	(3.16)	(0.68)	(0.13)	(2.14)	(0.43)	(-0.87)	(0.18)	(2.76)	(-0.66)	

Table 7. Sub-Period Analyses: High- vs Low-volatility Markets

One-month ahead index returns are regressed on the sample or implied correlation, along with other control variables across indexes for high- and low-volatility months. A month is classified as a high-volatility month if the monthly return volatility of the world market index in that month is above the median volatility of the world market index for the full sample. Accordingly, a low-volatility month has below-median volatility. Time-series averages of monthly regression coefficients and R^2 values are reported in the table. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panels A and C (B and D) show the results for high (low) volatility months for industry and country indexes, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*	*R²*
Panel A: Industry Indexes (High Volatility)											
-0.0112*	-	0.0057**	0.0099	0.0059***	0.0212*	0.0012	-0.0005	-0.0219	0.0076	0.0829**	0.1749
(-1.95)	-	(2.04)	(1.59)	(2.59)	(1.78)	(1.07)	(-0.90)	(-1.54)	(1.38)	(1.97)	
-	-0.0120**	0.0058**	0.0103*	0.0059**	0.0214*	0.0014	-0.0005	-0.0225	0.0073	0.0826**	0.1734
-	(-2.17)	(2.06)	(1.68)	(2.57)	(1.79)	(1.26)	(-0.92)	(-1.59)	(1.29)	(1.98)	
Panel B: Industry Indexes (Low Volatility)											
0.0011	-	0.0038	0.0056	-0.0039	0.0523***	0.0028	-0.0012	-0.0250	0.0110***	0.2652***	0.1610
(0.36)	-	(0.73)	(1.41)	(-0.76)	(3.15)	(1.41)	(-0.89)	(-0.88)	(3.28)	(4.37)	
-	0.0051*	0.0036	0.0045	-0.0039	0.0517***	0.0030	-0.0012	-0.0238	0.0111***	0.2682***	0.1611
-	(1.72)	(0.69)	(1.14)	(-0.76)	(3.14)	(1.47)	(-0.91)	(-0.84)	(3.32)	(4.46)	
Panel C: Country Indexes (High Volatility)											
-0.0046	-	0.0147	0.0009	0.0084	0.0606	0.0065	-0.0049	0.0418	0.0092	-0.1375*	0.4372
(-0.81)	-	(1.07)	(1.26)	(0.41)	(1.63)	(0.51)	(-1.06)	(0.74)	(1.37)	(-1.85)	
-	-0.0061	0.0141	0.0009	0.0094	0.0580	0.0078	-0.0059	0.0455	0.0082	-0.1390*	0.4360
-	(-1.11)	(1.03)	(1.31)	(0.47)	(1.59)	(0.60)	(-1.25)	(0.79)	(1.19)	(-1.85)	
Panel D: Country Indexes (Low Volatility)											
-0.0040	-	0.0674***	0.0001	-0.0224	0.0133	0.0011	-0.0039	-0.0434	0.0151*	-0.0592	0.4583
(-1.10)	-	(3.53)	(0.15)	(-0.90)	(0.31)	(0.08)	(-0.47)	(-0.73)	(1.67)	(-0.86)	
-	-0.0018	0.0702***	0.0000	-0.0222	0.0122	0.0008	-0.0036	-0.0394	0.0152*	-0.0500	0.4581
-	(-0.50)	(3.65)	(0.06)	(-0.89)	(0.28)	(0.05)	(-0.43)	(-0.68)	(1.68)	(-0.74)	

Table 8. Subsample Analyses: Emerging vs Developed Markets

One-month ahead index returns are regressed on the sample or implied correlation, along with other control variables across indexes for the subsamples of emerging and developed markets. Time-series averages of monthly regression coefficients and R^2 values are reported in the table. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panels A and B (C and D) show the results for industry (country) indexes from emerging and developed markets, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*	*R²*
Panel A: Industry Indexes from Emerging Markets											
-0.0109***	-	0.0146**	-0.0468	0.0046	0.0383***	-0.0008	-0.0010	-0.0039	0.0106***	0.2052***	0.1666
(-2.79)	-	(2.18)	(-0.77)	(0.73)	(2.93)	(-0.24)	(-0.83)	(-0.14)	(2.99)	(5.98)	
-	-0.0075**	0.0144**	-0.0576	0.0040	0.0403***	-0.0005	-0.0009	-0.0035	0.0105***	0.2066***	0.1658
-	(-2.07)	(2.17)	(-0.93)	(0.63)	(3.11)	(-0.15)	(-0.80)	(-0.12)	(2.93)	(6.05)	
Panel B: Industry Indexes from Developed Markets											
-0.0035	-	0.0093***	0.0050	-0.0003	0.0431***	0.0008	-0.0005	-0.0066	0.0139***	0.1194***	0.1665
(-1.16)	-	(2.71)	(1.57)	(-0.13)	(3.35)	(0.45)	(-0.60)	(-0.58)	(4.54)	(3.14)	
-	-0.0027	0.0094***	0.0047	-0.0004	0.0428***	0.0010	-0.0005	-0.0063	0.0135***	0.1217***	0.1667
-	(-0.94)	(2.74)	(1.48)	(-0.13)	(3.33)	(0.56)	(-0.62)	(-0.55)	(4.29)	(3.21)	
Panel C: Country Indexes from Emerging Markets											
-0.0014	-	0.0444	0.0002	0.0117	0.0254	0.0011	-0.0091	0.0504	0.0100*	-0.0198	0.3071
(-0.35)	-	(1.62)	(0.01)	(0.33)	(0.84)	(0.06)	(-1.19)	(0.60)	(1.67)	(-0.36)	
-	-0.0002	0.0363	-0.0032	0.0114	0.0217	0.0029	-0.0098	0.0405	0.0096	-0.0036	0.3059
-	(-0.06)	(1.42)	(-0.18)	(0.34)	(0.72)	(0.16)	(-1.29)	(0.48)	(1.60)	(-0.07)	
Panel D: Country Indexes from Developed Markets											
-0.0073	-	0.0390**	0.0004	0.0022	0.0502	-0.0060	-0.0023	0.1159	0.0136**	-0.1105	0.2914
(-1.47)	-	(1.97)	(0.76)	(0.16)	(1.19)	(-0.55)	(-0.50)	(1.20)	(2.00)	(-1.39)	
-	-0.0055	0.0382**	0.0002	0.0013	0.0488	-0.0031	-0.0023	0.1037	0.0121*	-0.1140	0.2919
-	(-1.15)	(1.99)	(0.40)	(0.09)	(1.16)	(-0.29)	(-0.50)	(1.06)	(1.76)	(-1.50)	

Table 9. Subsample Analyses: Segmented vs Integrated Markets

One-month ahead index returns are regressed on the sample or implied correlation, along with other control variables across segmented or integrated indexes. Indexes are classified as segmented or integrated based on the segmentation measure of Bekaert et al. (2011), which is independent of correlations. Time-series averages of monthly regression coefficients and R^2 values are reported in the table. Newey and West's (1987) adjusted t-statistics are provided in parentheses. Panels A and C (B and D) show the results for segmented (integrated) indexes of the industry and country samples, respectively. ***, **, and * indicate significance at 1%, 5%, and 10% levels, respectively.

Panel A: Segmented Industry Indexes											
Sample Corr.	*Implied Corr.*	*EBITDA/EV*	*MV*	*ROE*	*EP*	*OP*	*INV*	*NSI*	*MOM*	*IVOL*	*R²*
-0.0077**	-	0.0055	0.0055	-0.0058*	0.0309***	0.0044**	-0.0005	-0.0050	0.0113***	0.1782***	0.1788
(-2.52)	-	(1.50)	(0.45)	(-1.73)	(3.29)	(2.13)	(-0.49)	(-0.22)	(3.66)	(5.03)	
-	-0.0060**	0.0055	0.0049	-0.0054	0.0310***	0.0044**	-0.0006	-0.0065	0.0112***	0.1797***	0.1783
-	(-1.98)	(1.49)	(0.40)	(-1.64)	(3.31)	(2.16)	(-0.58)	(-0.28)	(3.60)	(5.10)	
Panel B: Integrated Industry Indexes											
-0.0049*	-	0.0130***	0.0061**	0.0076**	0.3506***	-0.0013	-0.0008	-0.0081	0.0111***	0.0890***	0.1304
(-1.94)	-	(3.49)	(2.13)	(2.03)	(12.37)	(-0.64)	(-1.41)	(-0.41)	(3.88)	(2.99)	
-	-0.0038	0.0132***	0.0055**	0.0074**	0.3493***	-0.0011	-0.0008	-0.0081	0.0108***	0.0899***	0.1299
-	(-1.55)	(3.56)	(1.99)	(2.00)	(12.37)	(-0.55)	(-1.39)	(-0.41)	(3.75)	(3.02)	
Panel C: Segmented Country Indexes											
-0.0013	-	0.0660**	0.0133	-0.0082	0.0257	0.0104	-0.0076	-0.0875	0.0083	0.0066	0.6584
(-0.24)	-	(2.17)	(0.72)	(-0.36)	(0.65)	(0.69)	(-1.02)	(-0.56)	(1.15)	(0.09)	
-	0.0069	0.0666**	0.0132	-0.0061	0.0332	0.0106	-0.0114	-0.0188	0.0036	0.0204	0.6576
-	(0.92)	(2.25)	(0.69)	(-0.27)	(0.65)	(0.69)	(-1.46)	(-0.12)	(0.47)	(0.27)	
Panel D: Integrated Country Indexes											
-0.0038	-	0.0281	-0.0004	0.0213	0.2473***	0.0063	-0.0050	0.1084	0.0122*	-0.0527	0.5808
(-0.91)	-	(1.21)	(-1.14)	(0.97)	(3.22)	(0.41)	(-0.85)	(1.42)	(1.79)	(-0.89)	
-	-0.0033	0.0303	-0.0003	0.0150	0.2485***	0.0110	-0.0057	0.1190	0.0110	-0.0523	0.5797
-	(-0.82)	(1.27)	(-0.80)	(0.70)	(3.29)	(0.72)	(-1.00)	(1.54)	(1.63)	(-0.90)	

Appendix

Table A1. Country and Industry Coverage

This table lists the countries included in the study. *Starting Date* shows the earliest month that is included in a country's research period. *Number of Monthly Observations* is the total number of months for which data exist for at least one industry in a country. *Number of Month x Industry Observations* indicates the summation of industry observations over the months in a country. *Nonexistent Industries* are the ones that have no data for any of the months for a certain country. Industries are identified by the following numbers: 1) Oil and Gas, 2) Chemicals, 3) Basic Resource, 4) Construction and Materials, 5) Industrial Goods and Services, 6) Automobiles and Parts, 7) Food and Beverage, 8) Personal and Household Goods, 9) Health Care, 10) Retail, 11) Media, 12) Travel and Leisure, 13) Telecom, 14) Utilities, 15) Banks, 16) Insurance, 17) Real Estate, 18) Financial Services, 19) Technology

	Countries	Starting Date	Number of Monthly Observations	Number of Month x Industry Observations	Nonexistent Industries
1	Argentina	September-93	301	4524	9, 16, 19
2	Australia	July-90	339	5852	-
3	Austria	July-90	339	4648	10, 11, 19
4	Bahrain	January-04	177	1878	1, 2, 6, 8, 9, 11, 14, 19
5	Belgium	July-90	339	5638	6
6	Brazil	August-94	290	4446	-
7	Bulgaria	November-00	215	3164	-
8	Canada	July-90	339	6102	1
9	Chile	July-90	339	4840	6, 11, 16
10	China	August-93	302	3851	8
11	Colombia	April-92	291	2883	6, 8, 9, 11, 12, 16, 17
12	Croatia	November-05	155	2334	11, 14, 19
13	Cyprus	January-93	309	3836	1, 6, 9
14	Czech Republic	December-93	298	4503	6, 7, 16
15	Denmark	July-90	339	4311	3, 6, 12
16	Egypt	October-96	264	3338	11, 14, 16
17	Finland	July-90	339	5297	-
18	France	July-90	339	6232	-
19	Germany	July-90	339	6076	-
20	Greece	July-90	339	4913	6
21	Hong Kong	July-90	339	5624	-
22	Hungary	July-91	327	4334	3, 8
23	India	July-90	339	5786	-
24	Indonesia	July-90	339	2087	1, 6, 12, 14, 16, 17
25	Ireland	July-90	339	4577	2, 6, 14
26	Israel	February-93	308	5106	3, 6
27	Italy	July-90	339	6376	-
28	Japan	July-90	339	6441	-
29	Jordan	July-06	147	2321	6, 11, 19
30	Kuwait	January-04	177	2191	3, 6, 8, 11, 14, 19
31	Luxemburg	February-92	320	3753	2, 4, 6
32	Malaysia	July-90	339	5902	-
33	Malta	February-00	224	2140	2, 3, 6, 8, 9, 11, 14
34	Mexico	July-90	339	4737	19
35	Morocco	April-94	294	3420	8, 11
36	Netherland	July-90	339	6070	6
37	New Zealand	July-90	339	5219	-
38	Nigeria	October-09	108	1257	3, 6, 10, 11, 13, 14
39	Norway	July-90	339	4758	6
40	Oman	November-05	155	2170	6, 8, 9, 11, 17
41	Pakistan	August-92	314	4431	11, 17, 19
42	Peru	February-94	296	4384	6, 9, 19
43	Philippine	July-90	339	4590	6, 16
44	Poland	April-94	294	4284	-
45	Portugal	July-90	339	5198	16
46	Qatar	January-04	177	2188	2, 3, 6, 8, 12, 19
47	Romania	January-97	261	3702	11
48	Russia	February-98	248	2921	8, 11
49	Singapore	July-90	339	5454	6
50	Slovenia	January-99	237	3268	3, 17
51	South Africa	July-90	339	5252	6, 14
52	South Korea	July-90	339	5830	-
53	Spain	July-90	339	6132	-
54	Sri Lanka	July-90	339	5217	3
55	Sweden	July-90	339	5572	-
56	Switz	July-90	339	5579	-
57	Taiwan	July-90	339	4626	11, 14
58	Thailand	July-90	339	5681	-
59	Turkey	July-90	339	5978	-
60	United Arab Emirates	January-04	177	1909	2, 3, 6, 8, 10, 11, 19
61	United Kingdom	July-90	339	6441	-
62	United States	July-90	339	6441	-
63	Venezuela	February-94	296	3389	6, 9, 11, 12, 16, 19