Mean-Variance Convergence around the World

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Abstract

In this paper, we show (i) that the risk-return characteristics of our sample of 17 developed stock markets of the world have converged significantly toward each other during our study period 1974 – 2004, (ii) that the speed of convergence, however, varies greatly across individual markets, largely reflecting the 'initial position' of each market relative to the rest of markets in the risk-return space, and that (iii) the documented international convergence in risk-return characteristics is driven mainly by the declining 'country effect', rather than the rising 'industry effect', suggesting that the convergence is associated with international market integration. Specifically, we first compute the *risk-return distance* among international stock markets based on the Euclidean distance and find that the distance thus computed has been deceasing significantly over time, implying a mean-variance convergence. In particular, the average risk-return distance has decreased by about 43% over our sample period. Lastly, we document that the risk-return characteristics of our sample of 14 emerging markets have been converging rapidly toward those of developed markets in recent years. This development notwithstanding, emerging markets still remain as a distinct asset class.

Mean-Variance Convergence around the World

1. Introduction

Since the seminal works of Grubel (1968), Levy and Sarnat (1970), and Solnik (1974) were published, a strand of studies have documented that investors may enhance the risk-return efficiency of their portfolios by international diversification as opposed to purely domestic diversification. In principle, the gains from international diversification may stem from the relatively low correlation among international stock markets, as carefully documented by Heston and Rouwenhorst (1994), Griffin and Karolyi (1998), and others, as well as distinct risk-return characteristics of these markets.

As international capital markets are becoming more integrated, however, stock markets may start to behave in a more concerted manner. Longin and Solnik (1995), in fact, report that the average correlation of stock returns for seven major markets in their sample increased significantly over the period 1960–1990. They also find that the international correlation tends to rise when markets are volatile. King, Sentana, and Wadhwani (1994), on the other hand, examine sixteen developed stock markets during the period 1970-1988 and report that the average correlation among these markets increased around the 1987 global crash, but with no clear trend increase in the correlation. In a more recent study, Solnik and Roulet (2000) find that the average correlation of fifteen stock markets in their sample with the world market exhibits a weak positive trend, increasing from 66 percent in 1971 to 75 percent in 1998. While the exact magnitude of the increase in the international correlation depends on the study period and the composition of sample markets, the overall weight of existing evidences indicates that the international stock market correlation has increased in recent years.

With deepening international market integration, not only the correlation structure but also the risk-return characteristics of stock markets may have evolved over time. Considering that the investment opportunities facing investors depend on both the correlation and risk-return characteristics, it is important to understand how these parameters might have evolved over time. As previously discussed, existing studies address the changing nature of international correlation, but not that of risk-return characteristics. This paper purports to fill this gap in the literature.

Specifically, the objectives of this paper are to (i) study the historical evolution of the risk-return characteristics of international stock markets and (ii) investigate what drives the documented pattern of evolution. In doing so, we compute the 'risk-return distance' as a way of quantifying the degree to which a market differs from the rest of sample markets in terms of risk-return characteristics. In particular, we measure the risk-return distance based on the Euclidean distance, which is a popular method for measuring the degree of (dis)similarity in cluster analysis. Since neither asset pricing models nor return-generating factors are used in computing the risk-return distance, our method is essentially model-free. Also, our Euclidean distance approach can easily accommodate multidimensional attributes of the observations. Once the risk-return distance is measured, we then proceed to examine if there are statistically significant time-trends in the distance measures. Our focus is on identifying particular evolutionary patterns in the risk-return characteristics of international stock markets if there is any. Our sample comprises 17 developed and 14 emerging stock markets for which we can obtain long enough return series necessary for our analysis.

The key findings of our paper can be summarized as follows. First, the risk-return characteristics of our sample of 17 developed stock markets have converged significantly toward each other during the period 1974 – 2004. Specifically, the average risk-return distance among these markets has decreased by about 43% over our sample period. As a result, these markets have become much less distinctive from each other in terms of risk-return characteristics. This international risk-return convergence is driven by the dual convergences in the risk and return dimensions. The risk-return convergence documented in this study remains robust to the inclusion of the varying market conditions. However, the risk-return characteristics of stock markets tend to diverge internationally when markets are volatile, *ceteris paribus*. We also show that the risk-return convergence and the increasing international correlation, an often cited trend, are related but distinct phenomena.

Second, the speed of convergence is found to vary greatly across individual markets. In particular, the speed of convergence is highest for Hong Kong, Austria, and Ireland, and lowest for Belgium, the Netherlands, and the United States, with the rest of sample markets falling in the middle. Notably, the speed of convergence is essentially zero for Belgium, implying that the country is at the focal point of international convergence. Furthermore, the speed of convergence is found to be closely related to the initial distance of each individual market from the international average risk-return characteristic: the farther away a market was initially, the more rapidly it has been converging toward the international average. It is noted that Japan is the only market that exhibits a tendency to 'diverge' from the rest of our sample markets. This Japanese exception may be attributable to the prolonged depression of the country's stock market throughout the 1990s, a period when many other countries experienced bullish market conditions.

Third, in order to identify the main driver for the risk-return convergence documented in this study, we investigate the separate effects of country vs. industry on stock market returns. We basically repeat the convergence tests using two 'decomposed' return series, one representing country effect and the other industry effect. We employ the Heston and Rouwenhorst (1994) method for the decomposition. Our test results clearly indicate that the risk-return convergence is driven by the decreasing country effect, rather than the rising industry effect, consistent with the view that the convergence is associated with international market integration. The risk-return characteristics attributable to industry effect exhibit no significant time trend, either upward or downward.

Fourth, the risk-return characteristics of our sample of 14 emerging markets have been converging rapidly toward those of developed markets in recent years. However, the average risk-return distance for emerging markets still remains much greater than that for developed markets. As of the end of our sample period, i.e., the second half of 2004, the average risk-return distance for our sample emerging markets is about three times as great as that for our sample developed markets. In fact, if both developed and emerging markets maintain their respective speeds of convergence in the future, our time trend projections suggest that a full convergence will not be reached until around year 2022. If the pace of convergence slows down as integration proceeds, a full convergence will take longer. Consequently, the recent convergence notwithstanding, emerging markets can be regarded as an effective vehicle for international diversification, consistent with the findings of Goetzmann, Li, and Rouwenhorst (2005) and others.

The rest of the paper is organized as follows. Section 2 describes the data and methodology. Section 3 provides tests of the mean-variance convergence among developed stock markets, whereas Section 4 investigates the driver of the mean-variance convergence documented in the previous section. Section 5 checks the robustness of the mean-variance convergence to the inclusion of the varying market conditions. In this section, we also briefly discuss the relationship between the increasing international correlation and the mean-variance convergence. Section 6 extends our analysis to a sample of emerging markets. Lastly, Section 7 offers summary and concluding remarks.

2. Data and Methodology

2.1. Data and Sample Selection

Our sample period for 17 developed markets spans January 1974 through December 2004. Our sample period starts in 1974 mainly because the process of capital market liberalization and integration began in earnest in the mid-1970s, following the collapse of the Bretton Woods system. With floating currency rates, countries face much reduced needs to control or regulate capital markets, launching the process of international financial integration. This process, in turn, might have changed the key characteristics of national stock markets over time. The 17 developed markets in our sample are: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, Singapore, South Africa, Switzerland, the United Kingdom, and the United States. These are the markets for which the data on stock market returns are available from DataStream for the entire sample period. We employ weekly stock market returns in conducting our analysis.

We also collect the data on local industry returns for each of our sample developed markets. We use 10 broad industry categories corresponding to the level 3 classification of industries provided by DataStream. The industry categories consist of resources, basic industries, general industries, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services, utilities, information technology, and financials.

For our sample emerging markets, we use the S&P/IFCG index returns during the period 1989 - 2004. The S&P/IFCG index was introduced by International Finance

Corporation (IFC) in 1981 and has been maintained by Standard & Poor's since 2000. The S&P/IFCG index targets an aggregate market capitalization of 70-80% of the total capitalization of all exchange-listed shares. The weekly S&P/IFCG index is available from December 1988.[1] We select 14 emerging markets for which the weekly S&P/IFCG indices are available from the inception. They are: Argentina, Brazil, Chile, Columbia, India, Jordan, Korea, Malaysia, Mexico, the Philippines, Taiwan, Thailand, Turkey, and Venezuela. All stock index returns are adjusted for dividends.

Figure 1 provides scatter plots of the risk-return characteristics of our 17 sample developed markets 'relative to' the cross-market average in three separate years, i.e., 1974, 1988, and 2003. For each year, the origin in the figure denotes (i) the cross-market average of mean returns and (ii) the cross-market average of standard deviations for 17 markets[2]. We use weekly dollar returns to compute these parameters. The y-axis thus measures how much the mean return for a market deviates from the cross-market average of mean returns during a particular year. Similarly, the x-axis measures how much the standard deviation for a market deviates from the cross-market average of standard deviations. For the U.S., for example, the mean and standard deviation of weekly returns were 0.46% and 2.18%, respectively, in 2003. For the same year, the cross-market average among the 17 sample markets was 0.71% for the mean and 2.46% for the standard deviation. The coordinates for the U.S, therefore, are –0.25% (= 0.46% - 0.71%)) on the y-axis and –0.28% (= 2.18% - 2.46%) on the x-axis for the year. As can be seen from Figure 1, the ellipse encompassing all the observations for each year becomes successively smaller over time. Our first look at the data, albeit cursory, thus suggests that the risk-return characteristics of international stock markets might have converged toward each other over time. In what follows, we formally investigate this possibility.

2.2. Methodology

[1] In choosing our sample period, we are also constrained by the fact that as we go back further, the number of emerging markets covered by the database declines sharply. For more information on the S&P/IFCG index, refer to its website (www.indices.standardpoors.com).

[2] There are two types of average in this study: one is the time series average for individual country during a certain period and the other is the cross-market average for sample markets. To avoid confusion, we need to clearly differentiate these two types. We thus adopt the convention of using (i) the term "mean" for each individual country and (ii) the term "average" for overall sample markets.

To formally test the risk-return convergence, we first introduce a risk-return distance measure, which is similar in concept to the (dis)similarity measure in cluster analysis. Cluster analysis is a term for a group of quantitative methods for examining multivariate data with a view to grouping the data based on the properties they have[3]. The main objective of cluster analysis is to define the structure of the data by placing the most similar observations into groups. It is thus necessary to measure (dis)similarities between observations as the first step to group the data.

One of the most commonly used methods for measuring (dis)similarities in cluster analysis is the Euclidean distance. Suppose that the number of characteristics for an observation is p and that each characteristic can be represented by a variable. Then, two observations can be represented by points in p-dimensions with coordinates (x_1, x_2, …, x_p) and (y_1, y_2, …, y_p) respectively. The Euclidean distance between two observations, d_{xy}, is computed by the following equation:

$$d_{xy} = \sqrt{\sum_{i=1}^{p}(x_i - y_i)^2} \tag{1}$$

The greater the Euclidean distance between the observations, the more dissimilar they are in terms of their characteristics. In our study, each market corresponds to an observation that is represented by two-dimensional characteristics, i.e., risk and return.

Applying the (dis)similarity measure in cluster analysis, we compute the risk-return distance for a particular market as the Euclidean distance between (i) a pair of mean return and standard deviation for a market and (ii) a pair of the cross-market average of mean returns and the cross-market average of standard deviations for N markets. For each market, we compute the risk-return distance for each observation period. To compute this distance measure, however, we first need to compute the return distance and risk distance measures separately.

We measure the ‘return distance’ of a market from the cross-market average for N markets based on the absolute difference between the mean return for the market and the cross-market average return. Specifically, the return distance for market i during the period t (DR_{it}) is computed as follows:

[3] For detailed description of cluster analysis, refer to Hair, Anderson, Tatham, and Black (1998) or Everitt, Landau, and Leese (2001).

$$DR_{it} = \left| \overline{R}_{it} - \frac{1}{N}\sum_{i=1}^{N} \overline{R}_{it} \right|, \text{ i = 1, …, N; t =1, …, T,} \tag{2}$$

where $\overline{R}_{it}$ is the mean return for market i during the period t. Similarly, we measure the 'risk distance' of a market based on the absolute difference between the standard deviation for the market and the cross-market average of standard deviations for N markets. The risk distance for market i during the period t (DS_{it}) is thus computed as follows:

$$DS_{it} = \left| SD_{it} - \frac{1}{N}\sum_{i=1}^{N} SD_{it} \right|, \text{ i = 1, …, N; t =1, …, T,} \tag{3}$$

where SD_{it} is the standard deviation for market i during the observation period t.

Since variables with larger dispersions would have a greater impact on the (dis)similarity measure than those with smaller dispersions, it is conventional in cluster analysis to normalize the variables before computing the (dis)similarity measure.[4] In computing the 'normalized risk-return distance', we use the proportion of a variable to the sum of the two variables as its weight. To be compatible with the Euclidean distance measure, we determine the weight for each variable as follows:

$$W(DR) = \sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 \Big/ (\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 + \sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2)} \tag{4}$$

$$W(DS) = \sqrt{\sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2 \Big/ (\sum_{i=1}^{N}\sum_{t=1}^{T} DR_{it}^2 + \sum_{i=1}^{N}\sum_{t=1}^{T} DS_{it}^2)} \tag{5}$$

where W(DR) is the weight for the return distance variable and W(DS) is the weight for the risk distance variable. We thus compute the risk-return distance (DRS_{it}) in such a way that each variable is normalized by its own weight:

$$DRS_{it} = \sqrt{AdjDR_{it}^2 + AdjDS_{it}^2} = \sqrt{(DR_{it} / W(DR))^2 + (DS_{it} / W(DS))^2}\ ,$$

$$\text{i = 1, …, N; t =1, …, T.} \tag{6}$$

[4] A popular method of normalization is the conversion of each variable to standard scores by subtracting the average and dividing by the standard deviation of each variable. However, this standardization method , that is referred to as autoscaling or standard scoring, cannot be applied directly to our two variables (DR_{it} and DS_{it}) because this standardization method would not preserve the dispersion structure in our data. In this paper, we are concerned with the time trend in the dispersion structure and thus need to preserve the dispersion structure.

Since we don't assume any asset pricing model or factors in computing the risk-return distance, our method is essentially model-free and highly robust.

Once we compute the risk-return distance for each market according to Equation (6), we compute the cross-market average (or median) of the risk-return distance measures for N markets for each period. We then examine if there is any time trend in the cross-market average (or median) risk-return distance. If the cross-market average (or median) risk-return distance shows a significant downward (upward) time trend, we will be led to conclude that the risk-return characteristics of international stock markets have converged (diverged), becoming more similar (dissimilar) to each other over time. We compute the distance measures for each six-month period during 1974 – 2004.

3. Evolution of the Risk-Return Characteristics among Developed Markets

In this section, we (i) compute the risk-return distance measures based on the formula developed in the previous section, (ii) test the convergence hypothesis, and (iii) discuss the factors related to the differential speed of convergence of individual stock markets toward the international average risk-return characteristic.

3.1. Time Trend in the Risk-Return Distance Measure

Table 1 reports the cross-market average of the risk-return distance (DRS) measures for 17 developed markets for each six-month period during 1974─2004. Table 1 also provides separately the cross-market average return distance (DR) and risk distance (DS) measures. All the distance measures reported here are computed based on the weekly stock market index returns in U.S. dollar terms. During our sample period 1974-2004, the average return distance is 0.35%, whereas the average risk distance is 0.65%. This means that during our sample period, the absolute difference between the return (standard deviation) for a typical market and the cross-market average return (standard deviation) is 0.35% (0.65%) per six-month period. Since the risk distance is substantially greater than the return distance, we normalize these distances so that the two variables may have similar impacts on the risk-return distance measure[5]. The cross-

[5] The weight used for normalization is 0.479 for the return distance (DR) and 0.878 for the risk distance (DS). It turned out, however, that the qualitative results of this paper do not depend on the normalization. The correlation between the cross-market average risk-return distance measures with and without normalization is 0.968 during our sample period.

market average of the risk-return distance (DRS) thus computed turns out to be 1.14% during our sample period.

As can be seen from Figure 2, which plots the cross-market average risk-return distance measure over time, there is a clear downward trend in the risk-return distance during our sample period. Figure 2 also shows that the risk-return distance measure fluctuates substantially about the time trend, probably reflecting the varying market conditions. Although unreported in the paper, we also notice quite similar downward time trends in both the return and risk distance measures. Our observations here thus suggest that the risk-return characteristics of international stock markets have become increasingly similar over time, and that this risk-return convergence reflects the dual convergences in the return as well as risk dimensions.

3.2. Tests of the Convergence Hypothesis

To formally test if there is indeed a significant time trend in the cross-market average (or median) risk-return distance measure, we estimate the following regression and check if the beta coefficient is significantly different from zero:

$$DRS_t = \alpha + \beta * \text{Time} + \varepsilon_t, \ \text{Time} = 1, \dots, 62 \tag{7}$$

We estimate the above time trend model using the distance measures computed from U.S. dollar returns as well as local currency returns in order to check if currency exchange rate changes might have affected the time trends in the distance measures.

When we test if a variable has a time trend, an appropriate test procedure depends on the property of error term. If the error term has a mild serial correlation, the standard test would be reliable. However, if the error term has a strong serial correlation or a unit root, the standard test performs poorly and the statistic from the test would not be reliable. For this reason, we first test if our sample has errors with a unit root. To this end, we employ the augmented Dickey-Fuller (ADF) test[6]. The null hypothesis of the ADF test is that errors from the regression model of Eq. (7) have a unit root with no constant or time trend[7]. If the null hypothesis is rejected, the statistic from the standard test is likely

[6] We also used a non-parametric unit-root test proposed by Breitung (2002) and obtained qualitatively similar results to those from the ADF test. The non-parametric test results are available upon request.

[7] The number of lags for the ADF test is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. The order of lag is reduced by one until the coefficient on the last included lag is found to be significant at the 10 percent level.

to be valid. For the standard test, we rely on the Newey-West heteroskedastic autocorrelation consistent t-statistics.

Table 2 reports test results for the convergence hypothesis for our sample developed markets. The table also reports separate test results for the return and risk convergences[8]. The test results with U.S. dollar returns are reported in Panel A, whereas those with local currency returns are reported in Panel B. It is first noted from Table 2 that for every regression, the ADF test rejects the null hypothesis that errors have a unit root at the 1 percent significance level, implying that the standard test is likely to be reliable. It is noted that for every distance measure, the coefficient of time variable (β) is negative and significant at the 5 percent level or better based on the Newey-West adjusted t-statistics, t_{HAC}. Thus, the test results presented in Table 2 lead us to conclude that the risk-return characteristics of 17 sample markets have converged significantly toward each other during our sample period and that this international risk-return convergence is driven by the dual convergences in return and risk distances. Furthermore, the above conclusion holds, regardless of whether the risk and return distances are measured in U.S. dollar or local currency terms. In fact, the test results presented in Panel B for local currency returns are almost identical to those in Panel A for U.S. dollar terms, implying that exchange rate changes have no noticeable effects on the evolutionary pattern of the risk-return characteristics of international stock markets during our sample period. In what follows, we examine the convergence issues with U.S. dollar returns.

The documented risk-return convergence is also economically significant. The intercept of the regression can be interpreted as the projected 'initial' risk-return distance

[8] As an alternative approach to examining the convergence in risk and return, we also use the so-called σ-convergence. This convergence measure has been extensively used in the economic growth literature (for the literature review on growth economics and concepts of convergence in the literature, refer to Durlauf and Quah (1999)). In a study of convergence in economic growth across the United States and European regions, Barro and Sala-i-Martin (1991) introduced the concept of σ-convergence. In their paper, σ-convergence is said to occur when the cross-sectional standard deviation of per capita income among regions diminishes over time. Under this definition, diminishing cross-sectional standard deviation for standard deviations or returns over time can be interpreted as evidence of the convergence for risk or return. The results from this approach are qualitatively similar to those from the Euclidean distance adopted by the current paper and available upon request. The disadvantage of σ-convergence is that it cannot simultaneously consider multivariate attributes of the observation. The Euclidean distance approach does not suffer from this problem.

from the cross-market average risk-return characteristic, whereas the slope may be interpreted as the speed of convergence toward the cross-market average. As shown in Panel A of Table 2, the projected 'initial' risk-return distance from the cross-market average is 0.01452. On the other hand, the projected risk-return distance from the cross-market average for the last observation period, i.e., the second half of 2004, is 0.00832. This implies that the average risk-return distance has decreased by about 43 percent over our sample period 1974─2004. International stock markets thus have become substantially less distinctive from each other in terms of risk-return characteristics.

Having established a significant risk-return convergence at the market average level, we now examine the issue at the individual market level. To test the convergence hypothesis for an individual market, we estimate the time trend model of Eq. (7) with the risk-return distance measure for the individual market, rather than the cross-market average distance, as the dependent variable. It is recalled that the risk-return distance for an individual market is computed according to Eq. (6).

Table 3 presents the test results of risk-return convergence for each of the 17 individual markets. Since the ADF test rejects the null hypothesis that errors have a unit root at least at the 5 percent significance level for each market, we rely on Newey-West adjusted t-statistics for interpreting our estimation results. For the risk-return distance measure (DRS), we reject the null hypothesis that there is no convergence at the 10 percent level or better for 11 out of 17 markets. The 11 markets exhibiting a significant risk-return convergence are: Australia, Austria, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Switzerland, and the United Kingdom. Four markets, i.e., the Netherlands, Singapore, South Africa, and the United States, exhibit a convergent tendency, albeit insignificant. Notably, the time trend coefficient (β) is essentially zero for Belgium. This implies that Belgium is at the focal point of international convergence. One market, Japan, is found to exhibit a statistically significant tendency to 'diverge' from the rest of the sample markets in terms of risk-return characteristics. This unusual result for Japan is driven by the return divergence; the Japanese risk distance exhibits a convergence, albeit statistically insignificant. The Japanese return divergence, in turn, is attributable to the prolonged depression of Japanese stock market throughout the 1990s when other markets experienced bullish conditions.

For the return distance (DR), we reject the null hypothesis of no convergence for 8 out of 17 markets at the 10 percent level or better[9]. For the risk distance (DS), on the other hand, we reject the null hypothesis for 7 out of 17 markets at the 10 percent level or better[10]. As can be seen from the F-test results provided in the last row of Table 3, we reject the hypothesis that all the time trend coefficients for 17 markets are jointly zero for each distance measure. In testing the hypothesis, we choose to employ the F statistic proposed by Vogelsang and Franses (2005)[11]. Overall, our test results in Table 3 show that the risk-return convergence among our sample markets is not driven by a few outlier markets. It is noted, however, that not all individual markets are expected to converge toward the international average since some markets can be near the focal point of convergence, to begin with.

We also perform pair-wise tests for the equality of time trend parameters (or speed of convergence) among 17 individual markets. Appendix A provides the test results. As can be seen from the appendix, for the U.S., we reject the null hypothesis of equal time trend β with the following eight markets: Australia, Austria, Canada, Denmark, Hong Kong, Ireland, Italy, and Japan. The null hypothesis cannot be rejected for the other eight markets. For Hong Kong, the null hypothesis of equal β is rejected with all other countries except Austria. For Japan, the null is rejected with all other markets except Belgium.

3.3. Factors Related to the Speed of Convergence

Our results in Table 3 clearly show that the speed of convergence varies greatly across individual markets. This situation means that the risk-return characteristics of individual markets have been evolving toward the international average, but at quite different paces. Given that the speed of convergence or the time trend coefficient (β) varies greatly across individual markets, it seems logical to ask the following question: What factors are related to the speed of convergence?

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[9] The eight markets are Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, and the United Kingdom.

[10] The seven markets are Australia, Austria, Denmark, Germany, Hong Kong, Ireland, and Switzerland.

[11] Vogelsang and Franses test has better finite sample size than the traditional Wald test, given that the series with deterministic trends have stationary errors. Vogelsang and Frances (2005), in fact, propose two F statistics. We use their second F statistic. They document that the size of the first and second F statistics are similar but the second statistic has a higher power, suggesting that the second F statistic is preferable.

It is first noted from Table 3 that the slope coefficient (β) appears to be correlated with the intercept (α) across markets. For instance, Belgium, the market with zero speed of convergence, has the lowest intercept (α) among all of our sample markets. By contrast, Hong Kong, the market with the most negative β, is found to be the one with the highest α. Canada has a medium β, coupled with a medium α. In order to verify this intriguing association, we plot the β coefficient against α coefficient for 17 individual markets in Figure 3. The figure indeed confirms that there is a rather strong negative relationship between the intercept and slope of the time trend regressions for our sample markets. As previously mentioned, the intercept of the regression can be interpreted as the projected 'initial distance' of an individual market from the cross-market average risk-return characteristic, whereas the slope may be interpreted as the speed of convergence of the market toward the international average. To be precise, the speed of convergence is the negative of the slope, i.e., (-1)β.

In light of the above interpretation, the strong negative relationship between the intercept and slope of the time trend regression illustrated in Figure 3 implies the following: The farther away a market was initially from the rest of markets in terms of risk-return characteristics, the faster the market converges toward the cross-market average. Accordingly, individual markets such as Hong Kong and Austria have both a high intercept and high speed of convergence, whereas such markets as Belgium, the Netherlands, and the U.S. have both a low intercept and low speed of convergence.

There are groups of countries for which we observe similar initial distances from and the speeds of convergence toward the cross-market average risk-return characteristic. For example, France and Germany show similar initial distances from and the speeds of convergence toward the cross-market average. We also see a similar pattern for the U.K., and Ireland. Geographical proximity, however, does not always imply similar α-β combinations. For example, the U.S. has a α-β combination that is very close to that of the Netherlands but significantly different from that of Canada. It is interesting to note that Canada exhibits a significant risk-return convergence toward the cross-market average, whereas the U.S. does not.[12]

[12] Jorion and Schwartz (1986) document that the Canadian and U.S. stock markets were segmented during their sample period 1968 – 1982. Mittoo (1992) finds that the two North American stock markets were

Next, we further investigate what other factors may be related to the speed of convergence. We consider the size of equity market, the ratio of equity market capitalization to GDP, dividend yield, and the ratio of exports plus imports to GDP as other possible explanatory variables. We expect that smaller markets may adjust more than larger markets as markets become integrated. We compute the mean equity market capitalization of each market during our sample period and use the logarithm of the mean equity market capitalization as the size of the market. Bekaert and Harvey (1995) explore an asset pricing model where the likelihood of market integration is allowed to vary over time. In their analysis, two information variables, i.e., dividend yield and equity market capitalization as a proportion of GDP, are associated with the likelihood of market integration. They argue that dividend yields decrease and the ratio of market capitalization to GDP increases when markets become integrated. Thus, we expect that the speed of convergence may be higher for a market whose dividend yield (the market capitalization to GDP ratio) declines (rises) faster than other markets over time. On the other hand, Forbes and Chinn (2004) study what explains the linkage in bond and stock markets between countries and find that direct trade between countries is the most important factor in determining the linkage in bond and stock markets. Motivated by their study, we include the ratio of exports plus imports to GDP as an additional explanatory variable. We expect that the speed of convergence would be higher, the faster a country's trade to GDP ratio increases relative to other countries.

Since we study the long-run trend of convergence, we also use the long-term trend in dividend yield, the ratio of stock market capitalization to GDP, and the ratio of trade to GDP for each market. To measure the long-term trends in these variables, we take a similar approach as we did for the risk-return distance. For dividend yield, we compute the mean monthly dividend yield for a market and calculate the absolute difference between the mean dividend yield for the market and the cross-market average dividend yield for 17 markets every year. Then we regress the absolute difference on the time variable and take the time coefficient as the long-run trend in dividend yield for the market. For the ratio of stock market capitalization to GDP (the ratio of trade to GDP),

segmented during the period 1977 – 1981 but became integrated later during the period 1982 - 86. These studies suggest that the Canadian and U.S. stock markets were different from each other in terms of risk-return characteristics at least during an earlier part of our sample period.

we compute the ratio of the mean stock market capitalization to GDP (the ratio of trade to GDP) for a market and calculate the difference between the ratio for the market and the cross-market average ratio for 17 markets every year. Then we regress the difference on the time variable and use the time coefficient as the long-run trend in the ratio of stock market capitalization to GDP (the ratio of trade to GDP) for the market[13].

Table 4 reports the regression results for the speed of convergence. The dependent variable in each regression is the estimated slope (β) from the risk-return convergence tests for individual markets in Table 3. The heteroskedasticity-robust t-values are reported in parentheses. In model 1, we regress the slope (β) on the intercept (α) from the risk-return convergence tests in Table 3. As we previously discussed, there indeed exists a strong negative relationship between the intercept and slope. The coefficient of the intercept (α) is significantly negative (t-statistic of -9.65) at the 1 percent level, with a R-square value of 0.698. In model 2, we regress the slope (β) on the market size. The coefficient of the market size is significantly positive at the 10 percent level, as expected, suggesting that smaller markets indeed adjust more and have steeper slopes than larger markets. In models 3 and 4 where we regress the slope (β) on the time trends of the ratio of stock market capitalization to GDP and dividend yield respectively, neither of the trend coefficients is found to be significant. When the slope is regressed on the time trend of the ratio of trade to GDP in model 5, we find a significant, negative coefficient. This implies that the more open a country becomes in terms of international trade, the faster converges the country's stock market toward other markets.

In model 6, we include all four additional factors, i.e., market size and trends in the ratio of market capitalization to GDP, dividend yield, and the ratio of trade to GDP, as independent variables. The ratio of trade to GDP is still significant at the 10 percent level, but the other three variables, including the market size variable, are insignificant. In model 7, we include the intercept (α) from the time trend regression as well as the four additional variables as independent variables. Estimation of the model shows that the intercept (α) is the only significant variable and dominates all the other variables. The

[13] We take the absolute difference for dividend yield while we just take the difference for stock market capitalization to GDP and trade to GDP. As a market becomes more integrated with other markets, we expect that the dividend yield for the market may become closer to those for other markets. On the other hand, the stock market capitalization to GDP and trade to GDP ratios for the market may become simply higher, not necessarily converging to other markets, as the market becomes more integrated.

ratio of trade to GDP becomes insignificant when considered with the intercept (α). This suggests that the trade to GDP ratio may have a high correlation with the intercept (in fact, 0.60) and proxy the latter to some extent. Overall, our regression analysis indicates that the initial risk-return distance from the international average mainly drives the speed of convergence of individual markets toward the international average.

4. What Drives the Risk-Return Convergence? Country vs. Industry Effects

Heston and Rouwenhorst (1994), Griffin and Karolyi (1998), and others find that the variation in national stock market returns can scarcely be explained by the industrial compositions of the economies. These studies maintain that low international correlations are mainly due to country factor, rather than industry factor. Recently, however, Baca, Garbe, and Weiss (2000) and Cavaglia, Brightman, and Aked (2000) report that the importance of industry factor has increased over time and that the impact of industry factor is nearly equal to or even larger than that of country factor. In a related study, Carrieri, Errunza and Sarkissian (2004) document that the industrial structure has become increasingly aligned across markets, especially across developed markets.

The aforementioned studies point to two possible drivers for the risk-return convergence among international stock markets: a decline in country effect or a rise in industry effect. If country effect has decreased over time as global capital markets have been integrating, we may observe a risk-return convergence. On the other hand, if the industrial structure across markets has become more similar and industry effect has increased, we may also observe a risk-return convergence. In this section, we investigate which of the two effects, country or industry, is the key driver for the risk-return convergence documented in the previous section. In tackling this question, we first generate two separate return series, one representing industry effect and the other country effect, for each market and conduct the convergence tests separately using each of the two return series.

Table 5 provides the industry composition of the DataStream stock market indices during the period 1974 – 2004. The average capitalization value of each market by industry is reported as percentage of the total market capitalization of 17 markets. As discussed in the data description, we use 10 broad industry categories corresponding to the level 3 industry classification provided by DataStream. The U.S. and Japan are the two dominant markets with the combined capitalization share of 71.78 percent (the US: 46.99 percent, Japan: 24.79 percent), followed by the U.K. (8.56 percent), Germany (4.16 percent), and France (2.61 percent). The industrial structure varies substantially across sample markets. Some markets have a well diversified industrial structure (e.g., France, Japan, and the U.S.), while others exhibit a more concentrated industrial structure (e.g., Hong Kong, South Africa, and Switzerland).

Following Heston and Rouwenhorst (1994), we decompose stock market returns into returns related to country and industry effects, respectively. Specifically, we run the following regression to decompose returns for industry j in country c (R_{cj}) into their industry and country components:

$$R_{cj} = \alpha + \beta_1 * I_1 + \beta_2 * I_2 + \ldots + \beta_{10} * I_{10} + \gamma_1 * C_1 + \gamma_2 * C_2 + \ldots + \gamma_{17} * C_{17} + e_{cj},$$
$$c = 1, 2, \ldots, 17; j = 1, 2, \ldots, 10, \qquad (8)$$

where I_j (C_c) is a dummy variable which takes the value of one if the return is from the industry j (country c) and zero otherwise. Since each return belongs to one country and one industry, the regression has a multicollinearity problem if dummy variables are defined for every country and industry. Again, following the lead of Heston and Rouwenhorst, we impose the constraint that the value-weighted sums of the industry and country coefficients equal to zero, respectively, to avoid this problem. Thus, we estimate the regression subject to the constraints that

$$\sum_{j=1}^{10} \omega_j \beta_j = 0, \text{ and}$$
$$\sum_{c=1}^{17} \lambda_c \gamma_c = 0,$$

where ω_j and λ_c are the weights of industry j and country c in the world market portfolio respectively.[14] Since the value-weighted sums of the industry and country coefficients equal to zero respectively, the intercept in the regression can be interpreted as the return on the value-weighted world market portfolio. The coefficient β_j can be interpreted as the estimated effect of industry j relative to the return on the world market portfolio.

[14] The world market portfolio here represents the total market capitalization of 17 countries in our sample. According to DataStream, the total market capitalization of 17 countries accounts for 87.1 percent of the actual world market capitalization as of the end of 2004.

Similarly, the coefficient γ_c can be interpreted as the estimated effect of country c relative to the return on the world market portfolio.

To address the issue of whether the risk-return convergence is driven by country or industry effect, we construct two hypothetical return series for each country – one with country effect and the other with industry effect – using the estimated coefficients of the regression. The hypothetical return for country c with country effect ($r_{c,ce}$) is computed as follows:

$$r_{c,ce} = \hat{\alpha} + \hat{\gamma}_c \text{, c = 1, 2, …, 17.} \tag{9}$$

On the other hand, the hypothetical return for country c with industry effect ($r_{c,ie}$) is defined as follows:

$$r_{c,ie} = \hat{\alpha} + \sum_{j=1}^{10} \chi_{cj} * \hat{\beta}_j \text{, c = 1, 2, …, 17,} \tag{10}$$

where χ_{cj} is the proportion of total market capitalization of country c in industry j. We separately test the convergence hypothesis using the two decomposed return series for 17 sample markets.

Figure 4 separately plots the time trends in the cross-market average of risk-return distance measures with country and industry effects. A few things are noteworthy from the figure. First, the magnitude of the risk-return distance with country effect is much greater than that with industry effect throughout the entire sample period. This implies that the distinct risk-return characteristics of national stock markets much documented in the literature are mainly attributable to country effect, rather than industry effect. What's more important, the risk-return distance measure with country effect clearly trends downward, exhibiting a convergence. By contrast, the risk-return distance measure with industry effect exhibits no clear time trend, either upward or downward. This sharply contrasting behavior implies that the risk-return convergence documented in the previous section is attributable to the declining country effect, rather than the rising industry effect.

Table 6 reports the test results for the convergence hypothesis with country and industry effects. Panel A provides the test results with country effect. The test results here are quite similar to those provided in Table 2. For each distance measure, the coefficient of the time trend variable is negative and significant at least at the 5 percent level, except for the cross-market median return distance. Panel B provides the test results with industry effect. It is striking that none of the time trend coefficients are significant. The test results provided in Panel B are qualitatively different from those in Panel A: For every distance measure, there is no convergence with industry effect alone.

Based on the test results presented in Table 6, we may conclude that the risk-return convergence among our sample markets is clearly attributable to the declining country effect, not the rising industry effect. From this conclusion, we may infer that the risk-return convergence is associated with international financial integration. As international capital markets become more integrated, the idiosyncratic factors of individual countries become less important over time, resulting in a convergence in risk-return characteristics among national stock markets. Indeed, our unreported results show that the cross-market average variance of residuals from the world market model for 17 sample markets has significantly decreased over our sample period.

5. Discussions

In this section, we discuss two issues related to the risk-return convergence. First, we check if the risk-return convergence remains robust to the inclusion of the variables representing the overall market conditions, such as the world market volatility and the bullish vs. bearish market conditions. Second, we examine whether the risk-return convergence documented in this study is really another manifestation of the increasing international correlation, a widely recognized phenomenon.

5.1. The Risk-Return Convergence Under Different Market Conditions

Previous studies document that there exists an asymmetry in the correlation of international stock markets under different market conditions: The correlation is higher under bearish market conditions than under bullish conditions (e.g. Longin and Solnik (2001)). In this subsection, we study if there is such an asymmetry in the risk-return distance measure. To investigate this issue, we introduce a dummy variable of 'down' which takes the value of one if the mean of weekly world market returns for a semi-annual period is negative, and zero otherwise[15]. We also check the effect of the world market volatility on the risk-return distance.

To formally test the convergence hypothesis while controlling for the varying world market conditions, we regress the cross-market average (or median) risk-return distance measure (DRS) on the time variable, standard deviation of the world market returns, 'down' dummy variable, and the interaction term between the standard deviation of the world market returns and the dummy variable:

$$DRS_t = \alpha + \beta_1 * \text{Time} + \beta_2 * SD_t(\text{World}) + \beta_3 * \text{Down}_t + \beta_4 * SD_t(\text{World}) * \text{Down}_t + \varepsilon_t, \quad t = 1,...,62. \qquad (11)$$

Table 7 reports the test results of the convergence hypothesis under different market conditions. As can be seen from the table, the time trend coefficient is still negative and significant at the 1 percent level for both the average and median risk-return distance measures, confirming that the risk-return characteristics have indeed converged during our sample period. Notably, the coefficient for the standard deviation of the world market return, SD(World), is found to be positive and significant at the 5 percent level or better. This implies that the risk-return distance becomes greater when the world market is more volatile. In contrast, the down dummy variable is found to be insignificant, implying that there would be no asymmetry in the risk-return distance across bullish vs. bearish market conditions. Since the interaction term also turns out to be insignificant, the effect of the world market volatility would not be asymmetric across bullish vs. bearish market conditions. Overall, the time trend together with the world market volatility substantially explains the time series behavior of the risk-return distance in the world market.

Table 7 also reports separately the test results of the convergence hypothesis under different market conditions for both the risk and return distances. As is the case with the risk-return distance measure, we still observe the risk and return convergences under different market conditions. The time trend coefficient is negative and significant at least at the 5 percent level for both the risk and return distance measures. Also, both the risk and return distances become greater when the world market is more volatile. It is

[15] Among 62 semi-annual periods in our sample, the mean of weekly world market returns is negative for 17 periods and positive for 45 periods.

noted that the coefficient on the standard deviation of the world market return is significantly positive at the 10 percent level or better. Unlike the case of the risk-return distance, the dummy variable is negative and significant at the 1 percent level for the risk distance, implying that the risk distance becomes smaller under the bearish market condition than under the bullish one. For the return distance, however, the dummy variable is insignificant. The interaction term is significantly negative for the return distance but positive for the risk distance, suggesting that the effect of the world market volatility is asymmetric under the bullish vs. bearish market conditions. It is noted that during our sample period, the standard deviation of the weekly world market return is 2.37% when the world market return is negative and 1.51% when the world market return is non-negative.

5.2. Does the Increasing Correlation Imply the Mean-Variance Convergence?

As mentioned previously, existing studies, e.g., Login and Solnik (1995), show that the correlation of international stock market returns has increased in recent years. Since international financial integration is often mentioned as an important force behind the increasing correlation, one may conjecture that the risk-return convergence documented in this study might be just another expression of the increasing correlation. In this subsection, we examine the relationship between the increasing correlation and the risk-return convergence using a market model and also provide empirical evidence showing that the increasing correlation does not necessarily imply the risk-return convergence.

Suppose that the return to an individual market i is a liner function of the world market return:

$$R_{it} = \alpha_i + \beta_i R_{Mt} + e_{it} . \qquad (12)$$

where Cov $(R_{Mt}, e_{it}) = 0$, and $E(e_{it}) = 0$. Obviously, this is the market model applied at the international index level.

Once the market model is assumed, the absolute difference in the expected return between market i and the world market is computed as follows:

$$|E(R_{it}) - E(R_{Mt})| = |\alpha_i + (\beta_i - 1)E(R_{Mt})|. \qquad (13)$$

Similarly, the absolute difference in the variance between market i and the world market is calculated as follows:

$$|Var(R_{it}) - Var(R_{Mt})| = |(\beta_i^2 - 1)Var(R_{Mt}) + Var(e_{it})|. \quad (14)$$

On the other hand, the correlation of returns between market i and the world market is computed as follows:

$$corr(R_{it}, R_{Mt}) = \frac{1}{\sqrt{1 + \dfrac{Var(e_{it})}{\beta_i^2 Var(R_{Mt})}}} \quad (15)$$

As can be inferred from Eq. (15), the correlation would always increase as the beta increases. However, an increase in the beta would have different effects on the absolute differences in the variance and in the expected return between market i and the world market, depending on the size of the beta. If the beta is greater (less) than unity, an increment in the beta would increase (decrease) the absolute differences in both the parameters. Therefore, the increasing correlation may not always be associated with the risk-return convergence in this simple model.

Japan provides empirical evidence supporting our simple analysis above[16]. As illustrated in Appendix B, Japan exhibits a risk-return 'divergence' from the rest of international markets and, at the same time, experiences the increasing correlation with other markets during our sample period. The Japanese case, albeit exceptional, clearly shows that the risk-return convergence may not always accompany the increasing correlation. Thus, the increasing correlation and risk-return convergence may be related but distinct phenomena.

6. Tests of the Convergence Hypothesis for Emerging Markets

In this section, we extend our analysis to a sample of emerging stock markets. Specifically, we examine if the risk-return characteristics of emerging markets have converged toward those of developed markets. As described in section 2.1, we use the weekly S&P/IFCG index returns for a sample of 14 emerging markets during the period 1989 – 2004.

In order to examine whether the risk-return characteristics of our sample emerging markets converge toward those of developed markets, for each 6-month period, we compute the absolute difference between the mean return (standard deviation) for an

[16] Appendix B simultaneously plots the time trends in the risk-return distance measure and the average international correlation for Japan.

emerging market and the cross-market average return (standard deviation) for 17 developed markets. We then calculate the cross-market average (median) risk-return distance measure for 14 emerging markets in the same way as explained in section 2.2[17].

Table 8 reports the results from formally testing if the risk-return characteristics of emerging markets have converged toward those of developed markets. The table also reports separate test results for the return convergence and risk convergence. As can be seen from Panel A of Table 8, the coefficient of the time variable is negative and statistically significant at the 5 percent level or better for each distance measure, with the sole exception of the cross-market median risk distance, This, of course, implies that the risk-return characteristics of our 14 sample emerging markets have been converging toward those of developed markets, and that the risk-return convergence reflects both the risk and return convergences.

The risk-return convergence of emerging markets is also economically significant. As can be seen from panel A of Table 8, the projected 'initial' average risk-return distance (i.e., the estimated intercept α) is 0.04657. By comparison, the projected average risk-return distance becomes 0.02705 in the last observation period, i.e., the second 6-month period of 2004. This means that the projected average risk-return distance of our sample emerging markets from the cross-market average of developed markets has decreased by about 42 percent over our sample period 1989 – 2004. It is also noteworthy that the average speed of convergence (the estimated β) for emerging markets, 0.00061, is about six times as fast as that observed for developed markets, 0.00010, during the period 1974 – 2004. The same point can be seen clearly from Figure 5, which separately illustrates the time trends in the average risk-return distances for both emerging and developed markets.

[17] Appendix C shows the time trends in the cross-market average risk-return distance measure and the average correlation for emerging markets. To compute the average correlation, we first compute the pair-wise correlation between each emerging market and each developed market for each six-month period. We then compute, for each period, the average of all the bilateral correlations between emerging and developed markets. As can be seen from the figure, there is a downward trend in the risk-return distance and an upward trend in the average correlation during the period 1989 – 2004. When the average correlation is regressed on the time variable, the intercept is 0.04199 and the time coefficient is 0.00882 (Newey-West t-statistic of 7.09). The time coefficient is significant at the 1 percent level. Thus, the projected initial average correlation is only 4.2 percent, but the projected average correlation increases to 32.4 percent for the second 6-month period of 2004.

Although the risk-return characteristics of emerging markets have converged rapidly toward those of developed markets in recent years, the former still remains substantially different from the latter. For instance, as of the end of our sample period, i.e., the second 6-month period of 2004, the projected average risk-return distance for emerging markets is about 0.027. This distance is still more than three times as great as the average distance for developed markets (0.008) observed during the same period, i.e., the second 6-month of 2004, and about twice as great as the projected risk-return distance for developed markets (0.014) at the start of our sample period, i.e., the first 6-month period of 1974. In other words, emerging markets have a long way to go before a full convergence would be reached. Figure 5 indeed shows that if both emerging and developed markets maintain their respective speeds of convergence in the future, a full convergence of the former toward the latter may occur in around year 2022. However, if the pace of convergence slows down as markets become more integrated, a full convergence would take longer.

Panel B of Table 8 presents the test results of the convergence hypothesis for individual emerging markets. For the risk-return distance measure (DRS), we reject the null hypothesis that there is no convergence for 4 out of 14 markets at the 10 percent level or better. The four emerging markets exhibiting a significant risk-return convergence toward developed markets are: Brazil, Chile, the Philippines, and Taiwan. In addition, six other markets (i.e., Argentina, Columbia, India, Mexico, Turkey, and Venezuela) exhibit a tendency to converge toward developed markets, albeit statistically insignificant. By contrast, four emerging markets, i.e., Jordan, Korea, Malaysia, and Thailand, exhibit a tendency to 'diverge' from developed markets in terms of risk-return characteristics, albeit statistically insignificant[18]. For the return distance (DR), we reject the null hypothesis of no convergence for 7 out of 14 markets at least at the 10 percent level[19]. For the risk distance (DS), on the other hand, we reject the null hypothesis of no convergence for 4 out of 14 markets at the 10 percent level or better.[20] One emerging

[18] As is the case with developed markets, there is a strong negative relationship between the intercept and slope of the regressions for 14 emerging markets. Detailed results are available upon request.
[19]The seven markets are Brazil, Chile, Mexico, Philippines, Taiwan, Turkey, and Venezuela.
[20] The four markets are Argentina, Brazil, Chile, and Taiwan.

market, Korea, exhibits a significant tendency to diverge from developed markets in terms of risk characteristic.

To help us better understand the risk-return characteristics of emerging markets relative to those of developed markets, we plot the risk-return distances of both emerging and developed markets from the cross-market average of 17 developed markets for year 2003. As can be seen from Figure 6, developed markets cluster together rather tightly around the cross-market average. In addition, five emerging markets (Columbia, Malaysia, Mexico, Philippines, and Taiwan) are located within the inner circle in Figure 6, clustering closely with developed markets. But the rest of emerging markets are scattered far afield from developed markets in the risk-return space. Even though the risk-return characteristics of emerging markets have converged rapidly toward those of developed markets in recent years, many emerging markets remain very much different from developed markets in terms of risk-return characteristics. Consequently, emerging markets can still be viewed as a distinct asset class and may serve as an effective vehicle for international diversification, consistent with the recent finding by Goetzmann, Li, and Rouwenhorst (2005).[21] It is also pointed out that due to the data requirement, our sample emerging markets are all relatively seasoned such markets. As the next wave of emerging/nascent markets become available for international investors, emerging markets may continue to be an effective vehicle for international diversification.

7. Summary and Concluding Remarks

In this paper, we documented a significant risk-return convergence among a sample of 17 developed markets during the period 1974─2004. The speed of convergence, however, varies greatly across individual markets, mainly reflecting the initial distances of individual markets from the international average risk-return characteristic. We also showed that the risk-return convergence among developed markets is attributable to the declining country effect, rather than the rising industry effect. From this result, we infer that international financial integration may be the main driver of the risk-return convergence. As international capital markets have become more

[21] Goetzmann, Li, and Rouwenhorst (2005) find that in recent years, the benefits from international diversification stem mainly from emerging markets.

integrated, the idiosyncratic ‘country’ factor of individual markets may have become less important over time, resulting in the international convergence in risk-return characteristics.

We also found that the time trend, together with the world market volatility, substantially explains the dynamics of the risk-return distance over time. The risk-return distance shows no asymmetric behavior under bullish vs. bearish market conditions. We further showed that the increasing correlation among markets, an often cited trend, and the risk-return convergence documented in this study are related but distinct phenomena. Finally, we documented that the risk-return characteristics of emerging markets have rapidly converged toward those of developed markets in recent years. The recent convergence notwithstanding, the majority of emerging markets still remain substantially different from developed markets in terms of risk-return characteristics, supporting the view of emerging markets as a distinct asset class.

To conclude, our paper showed how the key characteristics of national stock markets have evolved in a systematic fashion as international financial markets have been moving toward a greater integration, stimulating cross-border financial flows and interactions.

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Table 1. Cross-Market Average of the Risk-Return Distance Measures for 17 Developed Stock Markets, 1974 – 2004

The 17 developed markets in our sample are Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, Singapore, South Africa, Switzerland, United Kingdom, and United States. For each six-month period, the return (risk) distance for each market is computed during our sample period January 1974 – December 2004. The return distance for a market is computed as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. Stock market index returns in U.S. dollar terms, provided by DataStream, are used to compute the distances. All returns are adjusted for dividends.

Year	Semi-annual period	Risk-return distance (%)	Return distance (%)	Risk distance (%)	Year	Semi-annual period	Risk-return distance (%)	Return distance (%)	Risk distance (%)
1974	1	1.17	0.25	0.85	1990	1	1.12	0.32	0.72
	2	1.97	0.65	1.13		2	1.23	0.26	0.85
1975	1	2.31	0.63	1.56	1991	1	0.84	0.29	0.45
	2	0.86	0.25	0.55		2	0.69	0.23	0.36
1976	1	1.34	0.41	0.82	1992	1	0.86	0.31	0.41
	2	1.38	0.29	0.99		2	1.21	0.31	0.84
1977	1	0.98	0.30	0.58	1993	1	0.99	0.25	0.65
	2	1.18	0.45	0.53		2	1.02	0.36	0.50
1978	1	0.93	0.34	0.42	1994	1	1.04	0.31	0.61
	2	1.02	0.21	0.72		2	0.72	0.19	0.46
1979	1	0.93	0.27	0.55	1995	1	1.04	0.27	0.69
	2	1.26	0.44	0.65		2	0.50	0.17	0.25
1980	1	1.32	0.43	0.69	1996	1	0.70	0.15	0.52
	2	1.54	0.52	0.90		2	0.91	0.34	0.38
1981	1	1.91	0.66	0.97	1997	1	0.71	0.22	0.36
	2	1.29	0.35	0.81		2	1.46	0.52	0.75
1982	1	1.15	0.38	0.64	1998	1	1.78	0.60	0.98
	2	1.70	0.61	0.79		2	1.26	0.39	0.77
1983	1	1.07	0.26	0.66	1999	1	1.44	0.61	0.45
	2	1.24	0.33	0.78		2	0.86	0.30	0.44
1984	1	1.17	0.39	0.59	2000	1	1.04	0.32	0.55
	2	1.22	0.41	0.67		2	0.77	0.26	0.35
1985	1	1.54	0.53	0.77	2001	1	0.83	0.27	0.38
	2	1.63	0.61	0.71		2	0.86	0.25	0.46
1986	1	1.48	0.47	0.82	2002	1	0.81	0.26	0.46
	2	1.07	0.32	0.64		2	1.26	0.20	0.98
1987	1	1.21	0.48	0.43	2003	1	0.92	0.22	0.65
	2	1.91	0.28	1.53		2	0.57	0.13	0.38
1988	1	1.19	0.41	0.66	2004	1	0.53	0.14	0.30
	2	0.70	0.27	0.28		2	0.65	0.26	0.25
1989	1	1.19	0.38	0.63	Average		1.14	0.35	0.65
	2	0.97	0.28	0.57					

Table 2. Tests of the Convergence Hypothesis for 17 Developed Markets, 1974 - 2004

For each six-month period, the return (risk) distance for each market is computed. The return distance for a market is computed as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. We run the following regression for each dependent variable: Dependent variable = $\alpha + \beta$* Time + ε, Time = 1, … , 62. The t_{HAC} is the Newey-West heteroskedastic autocorrelation consistent t-statistic with a lag of 6. The augmented Dickey-Fuller (ADF) test is applied for testing the null hypothesis that the errors have a unit-root with no constant or time trend. The number of lags is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. In panel A, U.S dollar stock market index returns are used, whereas in panel B, local currency market index returns are used. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

Panel A. U.S. Dollar Index Returns

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.452	-0.010	-3.63***	0.236	-3.92***
	return distance	0.442	-0.003	-2.60**	0.156	-3.91***
	risk distance	0.855	-0.007	-3.79***	0.208	-7.00***
Cross-Market Median	risk-return distance	1.246	-0.008	-3.64***	0.210	-5.95***
	return distance	0.356	-0.002	-2.03**	0.101	-4.35***
	risk distance	0.698	-0.005	-3.66***	0.194	-6.36***

Panel B. Local Currency Index Returns

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.432	-0.010	-3.09***	0.218	-5.61***
	return distance	0.400	-0.003	-2.56**	0.166	-5.90***
	risk distance	0.864	-0.007	-2.71***	0.175	-6.20***
Cross-Market Median	risk-return distance	1.215	-0.008	-2.67***	0.185	-5.38***
	return distance	0.312	-0.002	-2.08**	0.114	-5.70***
	risk distance	0.722	-0.005	-2.51**	0.148	-6.17***

Table 3. Tests of the Convergence Hypothesis for Individual Developed Markets, 1974 – 2004

For each six-month period, the return (risk) distance is computed for each market. The return distance for a market is computed as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. The risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. The U.S dollar index returns are used. We run the following regression for each dependent variable: Dependent variable = $\alpha + \beta$* Time + ε, Time = 1, … , 62. The t_{HAC} is the Newey-West heteroskedastic autocorrelation consistent t-statistic with a lag of 6. The augmented Dickey-Fuller (ADF) test is applied for testing the null hypothesis that the errors have a unit-root with no constant or no time trend. The number of lags is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. We use the F statistic proposed by Vogelsang and Franses (2005) for testing the null hypothesis that all the time trend parameters are jointly zero. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

Market	Risk-return distance					Return distance					Risk distance				
	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)
Australia	1.429	-0.011	-2.69***	0.060	-7.19***	0.375	-0.002	-1.29	0.025	-7.83***	0.820	-0.007	-2.08**	0.043	-6.53***
Austria	2.142	-0.019	-2.85***	0.089	-6.11***	0.540	-0.003	-1.23	0.012	-2.92***	1.470	-0.017	-3.98***	0.172	-4.61***
Belgium	0.903	-0.000	-0.12	0.000	-5.44***	0.290	-0.001	-0.34	0.003	-4.78***	0.488	0.000	0.09	0.000	-7.95***
Canada	1.373	-0.009	-2.52**	0.093	-6.72***	0.440	-0.004	-2.51**	0.097	-3.52***	0.789	-0.005	-1.66	0.047	-5.68***
Denmark	1.157	-0.011	-2.78***	0.136	-5.99***	0.410	-0.004	-1.97*	0.076	-2.87***	0.634	-0.006	-2.53**	0.097	-5.76***
France	1.067	-0.009	-2.23**	0.076	-6.95***	0.456	-0.006	-3.25***	0.133	-7.01***	0.534	-0.004	-1.32	0.028	-4.41***
Germany	1.160	-0.008	-2.20**	0.073	-7.49***	0.340	-0.002	-1.75*	0.033	-4.40***	0.713	-0.005	-1.84*	0.070	-6.62***
Hong Kong	3.006	-0.030	-2.49**	0.123	-4.26***	0.872	-0.009	-2.99***	0.099	-4.76***	1.770	-0.017	-1.93*	0.080	-3.98***
Ireland	1.446	-0.016	-2.96***	0.168	-6.87***	0.550	-0.006	-2.35**	0.124	-2.56**	0.794	-0.010	-3.03***	0.137	-7.22***
Italy	1.835	-0.014	-1.71*	0.076	-4.24***	0.555	-0.005	-2.23**	0.081	-4.87***	1.002	-0.008	-1.26	0.037	-5.64***
Japan	1.107	0.005	1.88*	0.019	-7.67***	0.311	0.005	1.90*	0.052	-8.89***	0.722	-0.002	-0.63	0.004	-6.79***
Netherlands	1.142	-0.004	-1.53	0.027	-5.00***	0.203	-0.001	-1.10	0.014	-4.50***	0.677	-0.002	-0.54	0.005	-5.60***
Singapore	1.545	-0.010	-1.31	0.028	-6.18***	0.556	-0.004	-0.90	0.021	-6.30***	0.806	-0.006	-1.30	0.020	-7.15***
South Africa	1.804	-0.008	-1.31	0.022	-2.52***	0.557	-0.002	-0.67	0.006	-7.45***	1.105	-0.007	-1.43	0.032	-3.45***
Switzerland	1.085	-0.006	-2.55**	0.076	-7.71***	0.298	-0.001	-0.69	0.007	-8.14***	0.730	-0.007	-3.17***	0.147	-7.20***
U.K.	1.403	-0.015	-2.13**	0.148	-3.26***	0.492	-0.007	-3.46***	0.207	-8.33***	0.687	-0.005	-0.93	0.034	-3.07***
U.S.	1.179	-0.004	-1.16	0.023	-4.54***	0.250	0.000	0.25	0.001	-9.19***	0.797	-0.006	-1.61	0.053	-6.61***
F-test (H_0: All β's = 0)	597.08***					920.14***					465.73***				

Table 4. Regression Analysis of the Speed of Convergence: The Case of Individual Developed Markets

The dependent variable in each regression is the estimated slope (β) from the risk-return convergence tests for individual markets in Table 3. The intercept (α) is also from the risk-return convergence tests in Table 3. Log (Market Cap) is the logarithm of the mean equity market capitalization during the sample period. For the ratio of stock market capitalization to GDP [or the ratio of trade to GDP], we compute the ratio of the mean stock market capitalization to GDP [or the ratio of trade to GDP] for a market and calculate the difference between the ratio for the market and the cross-market average ratio for 17 markets every year. We then regress the difference on the time variable and use the time coefficient as an independent variable, Trend (Market Cap/GDP) [or Trend (Trade/GDP)] for the market. For dividend yield, we compute the mean monthly dividend yield for a market and calculate the absolute difference between the mean dividend yield for the market and the cross-market average dividend yield for 17 markets every year. We regress the absolute difference on the time variable and take the time coefficient as an independent variable, Trend (Dividend Yield) for the market. The heteroskedasticity-robust t-values are reported in parentheses. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

	Dependent Variable = Slope (β) from the Convergence Test						
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	0.00008 (3.08)***	-0.00034 (-2.98)***	-0.00010 (-5.56)***	-0.00009 (-3.99)***	-0.00010 (-6.68)***	-0.00032 (-2.02)*	-0.00012 (-0.79)
Intercept (α) from the Convergence Test	-0.01253 (-9.65)***						-0.01024 (-3.74)***
Log (Market Cap)		0.00002 (2.06)*				0.00002 (1.44)	0.00001 (1.18)
Trend (Market Cap/GDP)			-0.00104 (-0.94)			-0.00051 (-0.57)	-0.00023 (-0.47)
Trend (Dividend Yield)				0.03381 (0.76)		-0.01465 (-0.30)	-0.03520 (-0.85)
Trend (Trade/GDP)					-0.00358 (-3.91)***	-0.00263 (-1.83)*	-0.00077 (-0.56)
N	17	17	17	17	17	17	17
R^2	0.698	0.153	0.113	0.016	0.407	0.484	0.767

Table 5. Industry Compositions of 17 Developed Stock Markets

This table provides the average industry compositions of the DataStream market indices during the period 1974 – 2004. The average market capitalization of each market by industry is reported as percentage of the total market capitalization for 17 markets. We use 10 broad industry categories corresponding to the level 3 classification of industries provided by DataStream. The industry categories consist of resources, basic industries, general industries, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services, utilities, information technology, and financials

		Industry									
Market	Total	Resources	Basic Industries	General Industries	Cyclical Consumer Goods	Non-Cylical Consumer Goods	Cyclical Services	Non-Cycle Services	Utilities	Information Technology	Financials
Australia	1.41	0.50	0.16	0.04	0.01	0.11	0.19	0.05	0.01	0.00	0.34
Austria	0.11	0.01	0.02	0.01	0.00	0.01	0.00	0.00	0.01	0.00	0.04
Belgium	0.47	-	0.07	0.03	0.00	0.03	0.02	0.02	0.11	0.00	0.19
Canada	2.51	0.56	0.38	0.16	0.01	0.17	0.23	0.07	0.13	0.31	0.50
Denmark	0.29	-	0.01	0.02	0.01	0.07	0.09	0.02	0.00	0.00	0.06
France	2.61	0.34	0.26	0.37	0.25	0.40	0.25	0.23	0.01	0.15	0.36
Germany	4.16	0.00	0.68	0.97	0.47	0.20	0.16	0.25	0.20	0.08	1.15
Hong Kong	1.39	0.01	0.01	0.24	0.01	0.01	0.15	0.13	0.13	0.01	0.70
Ireland	0.15	0.00	0.04	0.00	0.01	0.03	0.01	0.00	-	0.00	0.07
Italy	1.46	0.08	0.07	0.07	0.17	0.01	0.07	0.22	0.06	0.01	0.69
Japan	24.79	0.39	3.38	3.04	2.54	1.79	3.27	1.23	1.45	1.54	6.16
Netherlands	2.08	0.68	0.10	0.18	0.02	0.29	0.18	0.08	-	0.03	0.54
Singapore	0.50	0.00	0.01	0.06	0.00	0.04	0.10	0.06	0.00	0.01	0.22
South Africa	0.88	0.57	0.02	0.10	0.00	0.06	0.03	0.01	-	-	0.10
Switzerland	1.65	-	0.08	0.14	0.02	0.86	0.06	0.02	0.04	0.00	0.42
U.K.	8.56	1.27	0.78	0.59	0.07	1.50	1.45	0.75	0.25	0.06	1.84
U.S.	46.99	5.05	3.08	4.26	2.22	8.39	5.74	3.84	3.16	5.96	5.27
Total	100.00	9.46	9.15	10.27	5.81	13.94	12.01	6.99	5.56	8.16	18.65

Table 6. Tests of the Convergence Hypothesis for 17 Developed Markets with Country and Industry Effects, 1974 - 2004

Following Heston and Rouwenhorst (1994), we separate out the country effect from the industry effect with the following regression: $R_{ci} = \alpha + \sum\beta_i{*}I_i + \sum\gamma_c{*}I_c + e_{ci}$. R_{ci} is the return for industry i of market c. I_i is a dummy variable, which takes the value of one if returns belong to industry i, or zero otherwise. I_c is a dummy variable, which takes the value of one if returns belong to market c, or zero otherwise. The regression is run weekly on the condition that the sum of the value-weighted country (industry) effect is zero. Returns with country (industry) effect are defined as the sum of the value-weighted return on the world market and return due to the country (industry) effect. We run the following regression for each dependent variable: dependent variable = $\alpha + \beta{*}$ Time + ε, Time = 1, … , 62. The t_{HAC} is the Newey-West heteroskedastic autocorrelation consistent t-statistic with a lag of 6. The augmented Dickey-Fuller (ADF) test is applied for testing the null hypothesis that the errors have a unit-root with no constant or time trend. The number of lags is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. For each six-month period, the return (risk) distance for each market is computed. The return distance for a market is defined as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. The risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. The U.S dollar stock market index returns are used to compute the distances. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

Panel A. Tests of the Convergence Hypothesis with Country Effect

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	1.358	-0.008	-2.88***	0.176	-5.39***
	return distance	0.429	-0.002	-2.44**	0.140	-4.25***
	risk distance	0.759	-0.005	-2.65**	0.121	-6.44***
Cross-Market Median	risk-return distance	1.099	-0.005	-2.39**	0.118	-5.31***
	return distance	0.341	-0.002	-1.64	0.066	-4.45***
	risk distance	0.622	-0.004	-3.20***	0.129	-6.45***

Panel B. Tests of the Convergence Hypothesis with Industry Effect

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	0.175	-0.00010	-0.09	0.000	-2.80***
	return distance	0.063	-0.00004	-0.01	0.000	-7.37***
	risk distance	0.086	0.00004	0.05	0.000	-2.80***
Cross-Market Median	risk-return distance	0.138	0.00004	0.31	0.006	-3.03***
	return distance	0.051	0.00008	0.22	0.001	-7.09***
	risk distance	0.059	0.00040	0.54	0.015	-4.09***

Table 7. Tests of the Convergence Hypothesis for 17 Developed Markets under Different Market Conditions, 1974 – 2004

This table reports the test results of the convergence hypothesis for 17 developed markets under different market conditions. The standard deviation of world market return is the standard deviation of weekly world market returns for a six-month period. Down is a dummy variable, which takes the value of one if the mean of weekly world market returns for any six-month period is negative, and zero otherwise. We run the following regression for each dependent variable: Dependent variable = $\alpha + \beta_1$* Time + β_2* SD(World) + β_3* Down + β_4* SD(World)*Down + ε, Time = 1, … , 62. The Newey-West t-statistics with a lag of 6 are reported in the parentheses. The augmented Dickey-Fuller (ADF) test is applied for testing the null hypothesis that the errors have a unit-root with no constant or time trend. The number of lags is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. For each six-month period, the return (risk) distance for each market is computed. The return distance for a market is defined as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. The risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. U.S dollar stock market index returns are used to compute the distances. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

	Dependent Variable	Intercept	Time	SD(World)	Down	SD(World) *Down	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market Average	risk-return distance	0.01048 (6.25)***	-0.00012 (-5.44)***	0.29253 (3.65)***	-0.00289 (-1.20)	0.04673 (0.46)	0.437	-4.07***
	return distance	0.00307 (5.03)***	-0.00003 (-3.26)***	0.09845 (3.49)***	0.00115 (1.01)	-0.09375 (-2.04)**	0.251	-4.02***
	risk distance	0.00629 (5.62)***	-0.00008 (-6.49)***	0.16259 (2.50)**	-0.00445 (-2.75)***	0.17476 (1.95)*	0.498	-4.69***
Cross-Market Median	risk-return distance	0.00973 (5.42)***	-0.00010 (-5.68)***	0.19642 (2.22)**	-0.00309 (-1.25)	0.09426 (0.86)	0.372	-6.71***
	return distance	0.00252 (3.55)***	-0.00002 (-2.37)**	0.07635 (2.22)**	0.00145 (1.23)	-0.10216 (-1.95)*	0.171	-4.37***
	risk distance	0.00547 (5.84)***	-0.00007 (-6.74)***	0.10953 (1.87)*	-0.00429 (-3.87)***	0.17982 (3.31)***	0.463	-6.47***

Table 8. Tests of the Convergence Hypothesis for 14 Emerging Markets, 1989 - 2004

For each six-month period, the return (risk) distance is computed for each market. The return distance for an emerging market is computed as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. The risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. We run the following regression for each dependent variable: Dependent variable = $\alpha + \beta$* Time + ε, Time = 1, … , 32. The t_{HAC} is the Newey-West heteroskedastic autocorrelation consistent t-statistic with a lag of 6. The augmented Dickey-Fuller (ADF) test is applied for testing the null hypothesis that the errors have a unit-root with no constant or time trend. The number of lags is determined by the method recommended in Campbell and Perron (1991). The maximum lag we consider is 6. We use the F statistic proposed by Vogelsang and Franses (2005) for testing the null hypothesis that all the time trend parameters are jointly zero. Statistical significance at the one, five and ten percent level is indicated by ***, **, and * respectively.

Panel A. Tests of the Convergence Hypothesis for 14 Emerging Markets toward Developed Markets

	Dependent Variable	Intercept(α)*100	Time(β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ statistic)
Cross-Market	risk-return distance	4.657	-0.061	-3.86***	0.281	-3.33***
Average	return distance	1.014	-0.013	-4.24***	0.234	-4.19***
	risk distance	2.725	-0.034	-3.13***	0.208	-3.53***
Cross-Market	risk-return distance	3.295	-0.033	-2.69**	0.153	-3.65***
Median	return distance	0.814	-0.012	-4.80***	0.252	-4.44***
	risk distance	1.459	-0.001	-0.09	0.000	-3.04***

Table 8. (Continued)

Panel B. Tests of the Convergence Hypothesis for Individual Emerging Markets toward Developed Markets

Market	Risk-return distance					Return distance					Risk distance				
	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)	Intercept (α)*100	Time (β)*100	t_{HAC} (Time)	R^2	Unit Root Test for Residuals (τ stat)
Argentina	10.434	-0.273	-1.54	0.185	-3.65^{***}	1.497	-0.028	-0.96	0.052	-4.74^{***}	8.148	-0.261	-2.05^{**}	0.329	-3.07^{***}
Brazil	9.412	-0.221	-4.20^{***}	0.349	-2.83^{***}	1.107	-0.020	-1.72^{*}	0.054	-4.29^{***}	6.755	-0.175	-4.58^{***}	0.410	-4.96^{***}
Chile	1.943	-0.037	-5.12^{***}	0.216	-6.66^{***}	0.756	-0.013	-3.15^{***}	0.103	-6.23^{***}	1.012	-0.020	-4.40^{***}	0.131	-5.32^{***}
Columbia	2.651	-0.035	-1.24	0.042	-4.93^{***}	0.878	-0.007	-0.75	0.010	-6.16^{***}	1.606	-0.030	-1.43	0.066	-4.26^{***}
India	2.711	-0.029	-0.92	0.032	-6.33^{***}	0.664	-0.001	-0.10	0.000	-6.66^{***}	1.781	-0.032	-1.32	0.061	-3.47^{***}
Jordan	1.311	0.009	0.79	0.014	-3.82^{***}	0.425	-0.002	-0.65	0.004	-4.10^{***}	0.632	0.014	1.36	0.050	-4.82^{***}
Korea	2.395	0.076	1.11	0.049	-3.35^{***}	0.813	0.002	0.12	0.001	-2.47^{**}	0.990	0.080	1.95^{*}	0.116	-2.96^{***}
Malaysia	2.016	0.014	0.26	0.002	-3.16^{***}	0.599	0.001	0.07	0.000	-3.91^{***}	0.953	0.017	0.47	0.007	-3.60^{***}
Mexico	3.184	-0.047	-1.13	0.073	-3.76^{***}	0.937	-0.019	-3.30^{***}	0.150	-6.04^{***}	1.363	-0.005	-0.11	0.001	-2.63^{***}
Philippines	3.411	-0.060	-1.99^{*}	0.096	-3.31^{***}	1.053	-0.020	-2.18^{**}	0.079	-4.99^{***}	1.889	-0.031	-1.63	0.049	-3.41^{***}
Taiwan	5.119	-0.117	-2.87^{***}	0.252	-5.69^{***}	1.122	-0.028	-2.61^{**}	0.156	-7.21^{***}	3.182	-0.068	-2.16^{**}	0.172	-4.05^{***}
Thailand	3.027	0.035	0.62	0.014	-2.70^{***}	0.774	0.012	0.78	0.017	-3.84^{***}	1.718	0.028	0.66	0.167	-2.57^{**}
Turkey	9.348	-0.087	-1.41	0.048	-6.65^{***}	1.957	-0.034	-3.28^{***}	0.154	-7.64^{***}	5.129	0.005	0.10	0.000	-5.20^{***}
Venezuela	6.025	-0.068	-1.42	0.033	-3.74^{***}	1.609	-0.032	-1.90^{*}	0.094	-6.05^{***}	2.999	0.002	0.04	0.000	-5.43^{***}
F-test (H_0: All β's = 0)	809.6^{***}					10842.9^{***}					874.5^{***}				

Figure 1. The Risk-Return Distance among 17 Developed Markets for 1974, 1988, and 2003

Figure 1 provides a snap shot of how much the risk-return characteristics of the 17 stock markets differ from each other in three separate years, 1974, 1988, and 2003. The origin denotes (i) the cross-market average of mean returns and (ii) the cross-market average of standard deviations for 17 markets. Weekly dollar returns are used to compute these parameters. The y-axis measures how much the mean return for a market deviates from the cross-market average of mean returns during a particular year. Similarly, the x-axis measures how much the standard deviation for a market deviates from the cross-market average of standard deviations. For each year, an ellipse is drawn to encompass all the observations for the year.

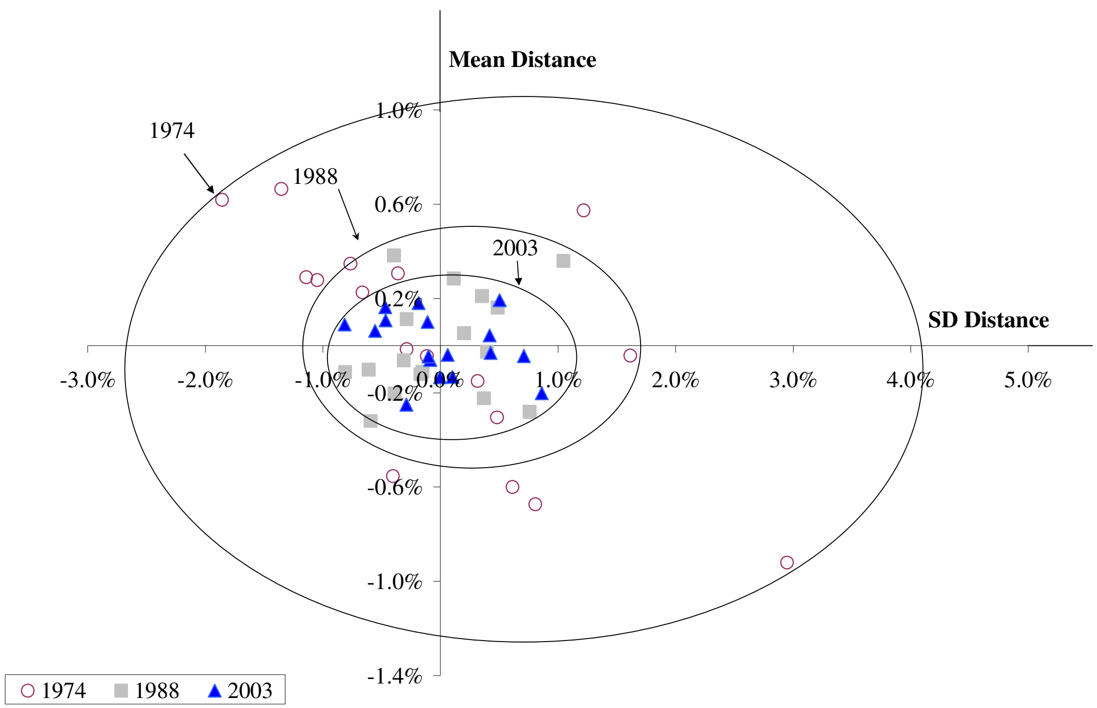


Figure 2. Time Trend in the Cross-Market Average Risk-Return Distance Measure for 17 Developed Markets

For each six-month period, the return (risk) distance for each market is computed. The return distance for a market is computed as the absolute difference between the mean of weekly returns for the market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for the market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. U.S. dollar market index returns are used to compute the distances.

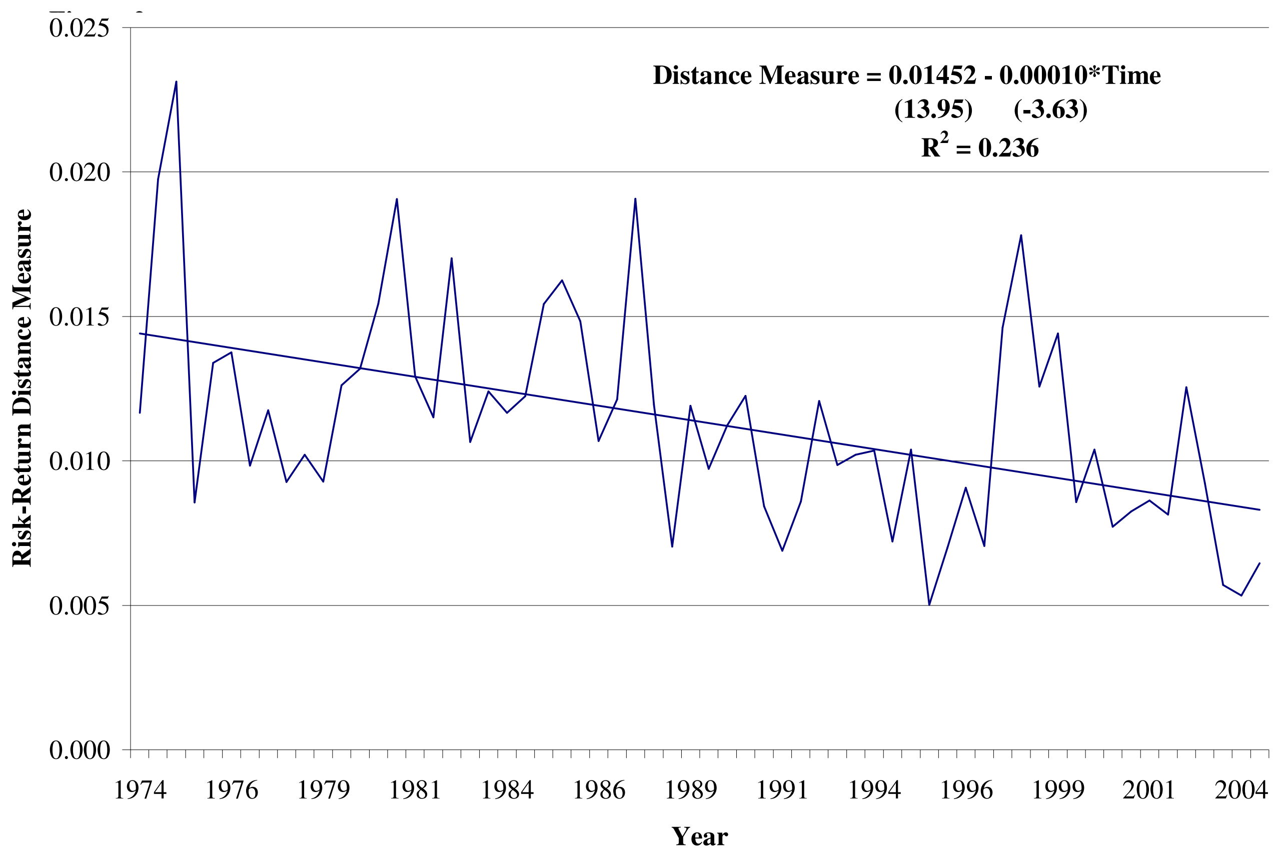


Figure 3. Relationship between the Intercept (α) and Slope (β) of Time Trend Regression of the Risk-Return Distance Measures for 17 Developed Markets

For each six-month period, the return (risk) distance for each market is computed. The return (risk) distance for a market is computed as the absolute difference between the mean (standard deviation) of weekly returns for the market and the cross-market average of mean weekly returns (standard deviations) for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. U.S dollar stock market index returns are used to compute the distances. Once the distances are computed, we estimate the following regression: Distance measure = $\alpha + \beta^{*}$ Time + ε, Time = 1, … , 62. Next, we regress the estimated slope coefficient (β) on the intercept (α) to examine the relationship between the two parameters.

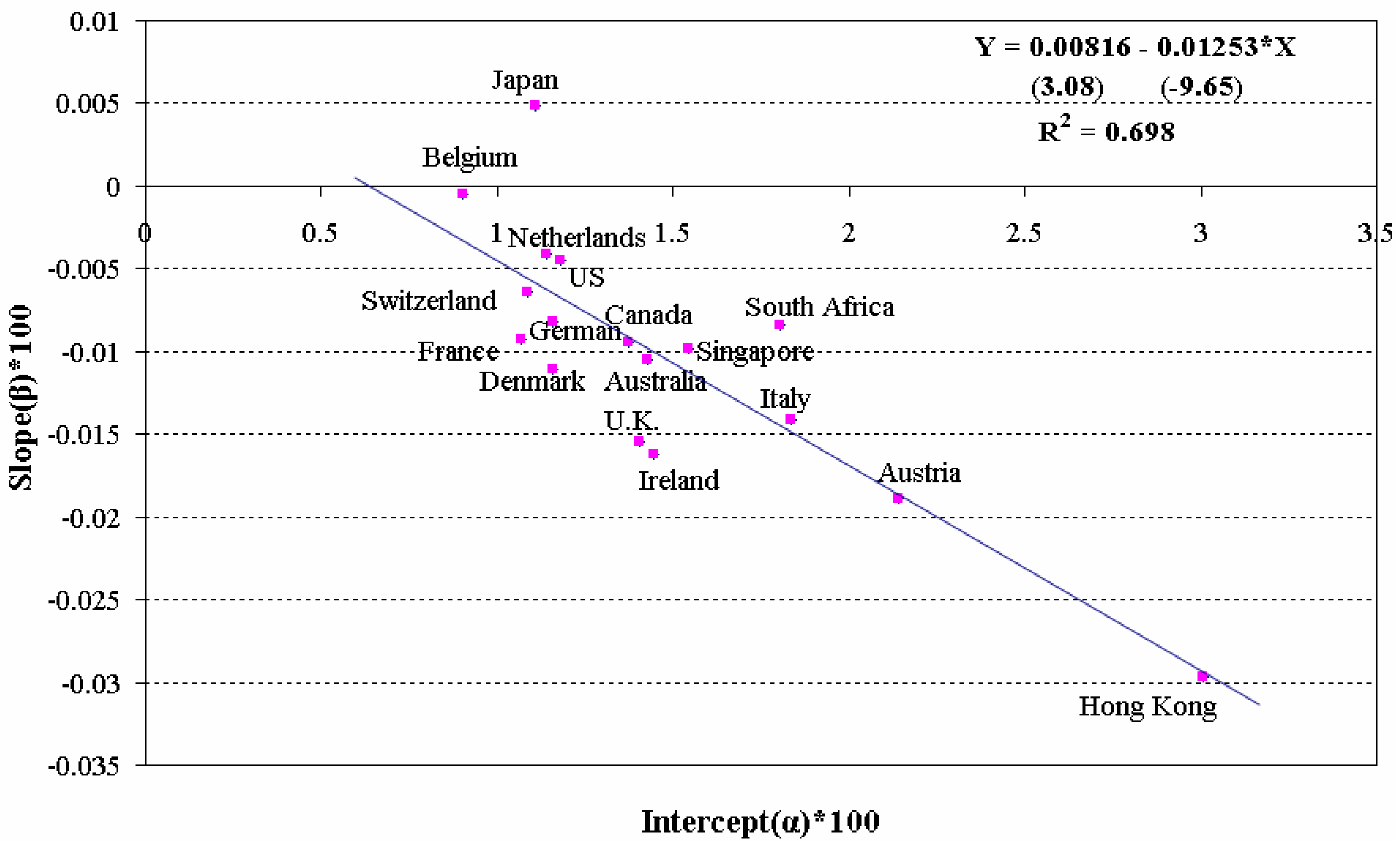


Figure 4. Time Trends in the Cross-Market Average of the Risk-Return Distance Measures for 17 Developed Markets: Country vs. Industry Effects

Following Heston and Rouwenhorst (1994), we separate out the country effect from the industry effect with the following regression: $R_{ci} = \alpha + \sum\beta_i*I_i + \sum\gamma_c*I_c + e_{ci}$, where R_{ci} is the return for industry i of market c; I_i is a dummy variable, which takes the value of one if returns belong to industry i, or zero otherwise; I_c is a dummy variable, which takes the value of one if returns belong to market c, or zero otherwise. We use 10 broad industry categories corresponding to the level 3 classification of industries provided by DataStream. The regression is run weekly on the condition that the sum of the value-weighted country (industry) effect is zero. Returns with country (industry) effect are defined as the sum of the value-weighted return on the world market and returns due to the country (industry) effect.

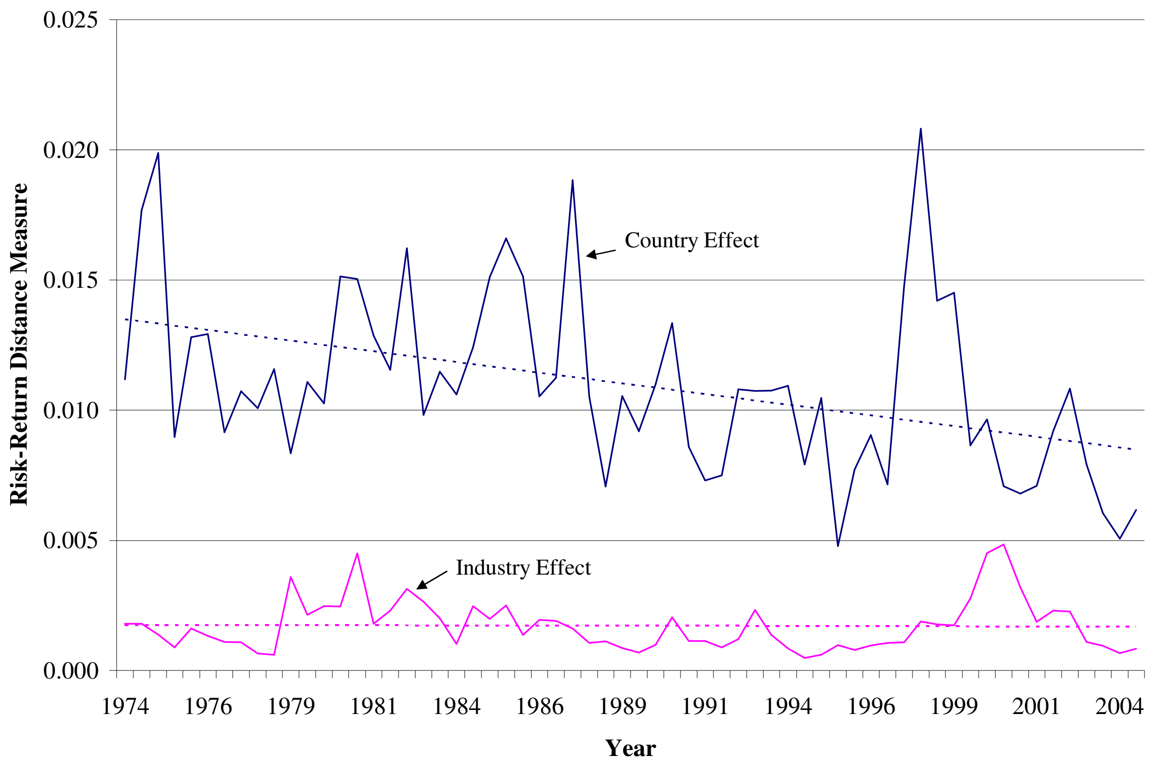


Figure 5. Time-Trend Projections of the Risk-Return Distances: Emerging vs. Developed Markets

This figure shows the linear time-trend projections of the cross-market average risk-return distances for 14 emerging and 17 developed markets. The risk-return distance is measured from the average risk-return characteristics for 17 developed markets. In order to project each linear trend, we use the intercept and slope from the following regression for the risk-return distance measure: Distance measure = $\alpha + \beta^*$ Time + ε. For each six-month period, return (risk) distance for each market is computed. The return distance for a market is computed as the absolute difference between the mean of weekly returns for each market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for each market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. The cross-market average risk-return distances for 14 emerging and 17 developed markets, which are dependent variables for the regression, are calculated separately. U.S dollar stock market index returns are used to compute the distances.

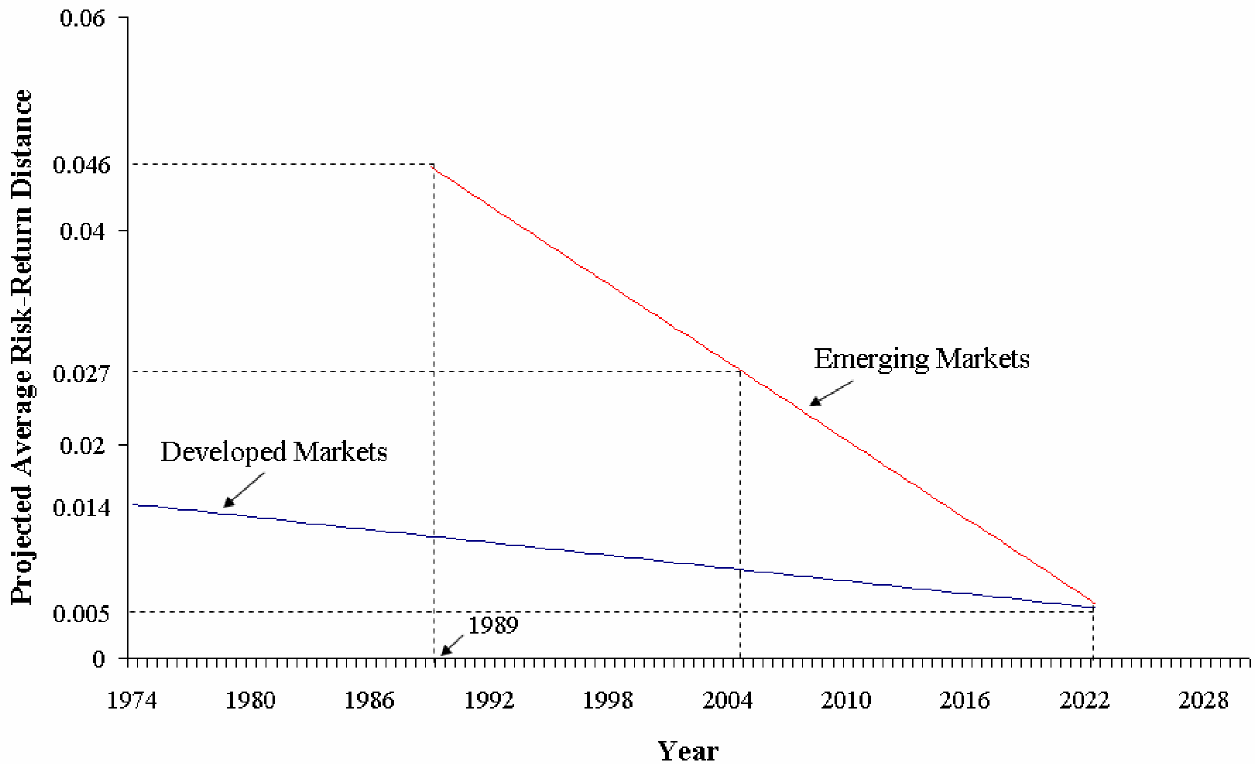
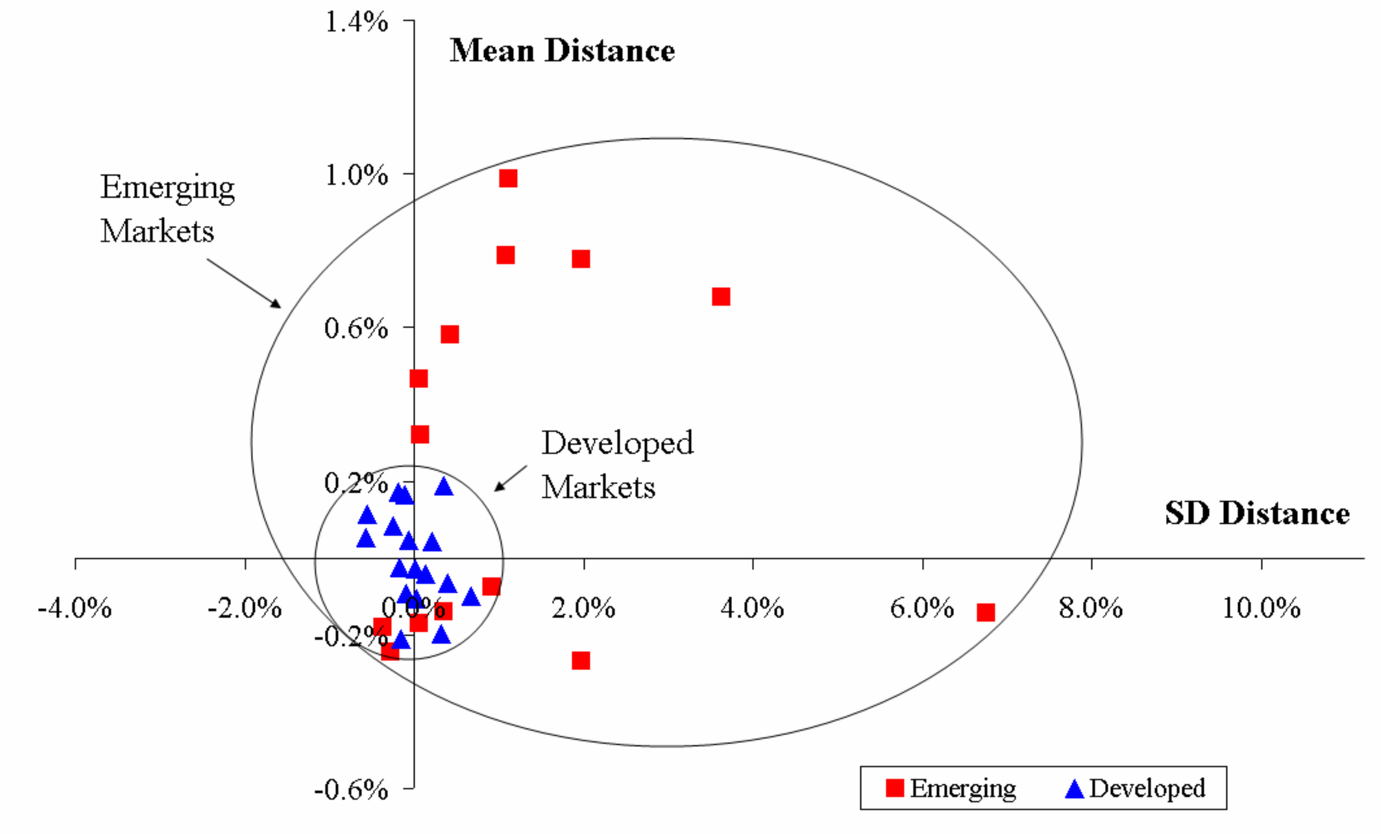


Figure 6. Risk-Return Distances from the Cross-Market Average of 17 Developed Markets for 2003: 17 Developed vs. 14 Emerging Markets

This figure shows how much the risk-return characteristics of the 17 developed and 14 emerging stock markets differ from each other in year 2003. The origin denotes (i) the cross-market average of mean returns and (ii) the cross-market average of standard deviations for 17 developed markets. Weekly dollar returns are used to compute these parameters. The y-axis measures how much the mean return for a market deviates from the cross-market average of mean returns. Similarly, the x-axis measures how much the standard deviation for a market deviates from the cross-market average of standard deviations.



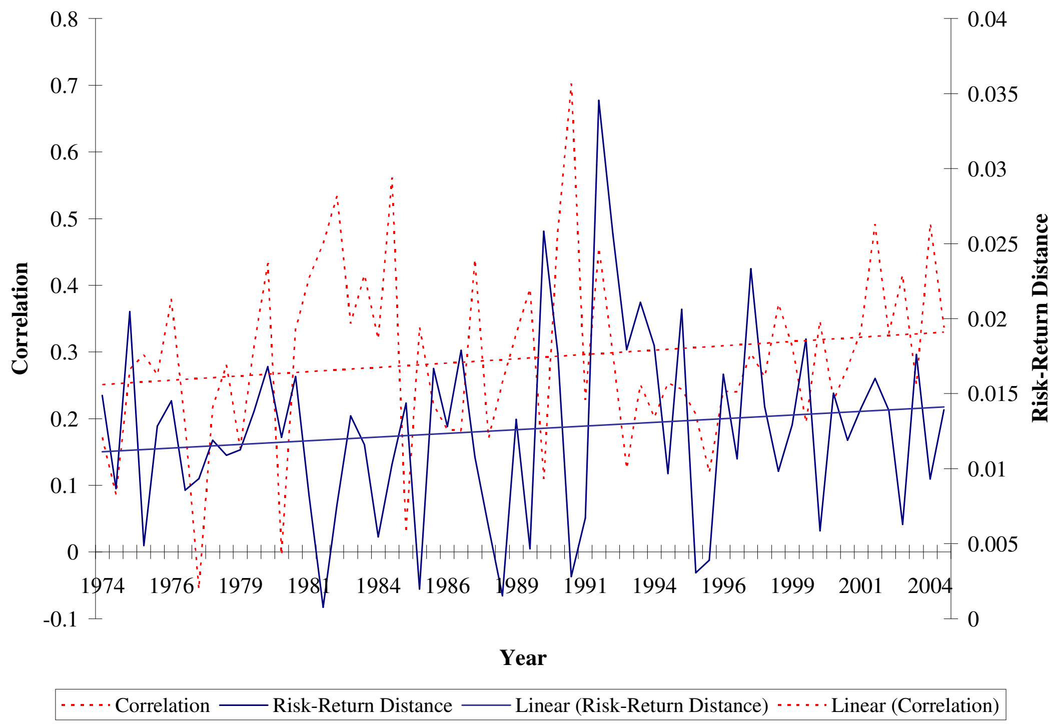
Appendix A. Pairwise Tests for the Equality of Time Trend Parameters Among 17 Individual Developed Markets

The following table reports pairwise test results for the equality of time trend parameters (β) for 17 markets. The 17 markets are Australia (AUST), Austria (ASTR), Belgium (BELG), Canada (CNDA), Denmark (DENM), France (FRNC), Germany (GERM), Hong Kong (HGKG), Ireland (IREL), Italy (ITAL), Japan (JPAN), Netherlands (NETH), Singapore (SING), South Africa (SOAF), Switzerland (SWIT), U.K., and U.S. The time trend parameters are obtained from the regressions of the risk-return distance measures as reported in Table 3. We use the F statistic proposed by Vogelsang and Franses (2005) for testing the null hypothesis that the two time trend parameters are equal to each other. The superscripts a, b, and c denote rejection of the null hypothesis at the 1 percent, 5 percent, and 10 percent level of significance, respectively. The critical values are 83.96, 41.53, and 20.14 at the 1 percent, 5 percent, and 10 percent level of significance, respectively.

	ASTR	BELG	CNDA	DENM	FRNC	GERM	HGKG	IREL	ITAL	JPAN	NETH	SING	SOAF	SWIT	U.K.	U.S.
AUST	24.60[c]	68.16[b]	1.10	0.92	0.82	4.49	102.87[a]	12.32	2.87	85.69[a]	53.99[b]	0.26	2.10	28.80[c]	4.96	28.51[c]
ASTR		47.73[b]	42.55[b]	18.65	12.22	19.73	11.94	0.92	3.34	92.50[a]	61.56[b]	12.98	13.98	31.49[c]	1.05	67.73[b]
BELG			29.34[c]	65.07[b]	316.74[a]	143.91[a]	315.18[a]	194.48[a]	29.16[c]	10.98	10.24	66.66[b]	47.83[b]	68.00[b]	87.02[a]	5.76
CNDA				4.04	0.01	0.75	103.30[a]	13.93	7.75	128.48[a]	49.86[b]	0.06	0.27	7.02	6.21	48.37[b]
DENM					1.67	5.78	118.37[a]	8.95	3.28	128.70[a]	73.94[b]	0.97	2.49	37.55[c]	3.57	59.30[b]
FRNC						1.79	114.87[a]	35.78[c]	3.67	80.46[b]	18.18	0.20	0.38	12.47	14.40	7.74
GERM							149.93[a]	98.92[a]	5.73	103.93[a]	24.40[c]	2.66	0.01	7.37	29.60[c]	5.54
HGKG								44.97[b]	44.93[b]	324.85[a]	203.75[a]	143.58[a]	126.05[a]	189.12[a]	38.47[c]	153.12[a]
IREL									0.55	242.50[a]	89.35[a]	27.64[c]	17.75	67.18[b]	1.00	32.43[c]
ITAL										107.28[a]	27.02[c]	3.02	3.57	13.85	0.16	49.37[b]
JPAN											85.16[a]	81.15[b]	29.31[c]	69.88[b]	136.15[a]	43.13[b]
NETH												19.55	5.52	8.38	37.50[c]	0.12
SING													0.81	9.65	12.38	8.26
SOAF														2.31	9.73	3.53
SWIT															24.78[c]	2.70
U.K.																16.83

Appendix B. Time Trends in the Risk-Return Distance Measure and the Average International Correlation: The Case of Japan

For each semi-annual period, the return (risk) distance is computed for Japan. The return distance for Japan is computed as the absolute difference between the mean of weekly returns for Japan and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for Japan is computed as the absolute difference between the standard deviation of weekly returns for Japan and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. Euclidean distance is used to measure the risk-return distance. For each semi-annual period, the correlation between weekly returns for Japan and those for each market is calculated. Then, the average correlation of 16 bilateral correlations is computed. U.S dollar stock market index returns are used to compute the distances and parameters.



Appendix C. Time Trends in the Cross-Market Average Risk-Return Distance Measure and the Average Correlation for 14 Emerging Markets

For each semi-annual period, the return (risk) distance is computed for each market. The return distance for a market is computed as the absolute difference between the mean of weekly returns for each emerging market and the cross-market average of mean weekly returns for 17 developed markets. Similarly, the risk distance for a market is computed as the absolute difference between the standard deviation of weekly returns for each emerging market and the cross-market average of the standard deviations for 17 developed markets. Before the risk-return distance measure is computed, the return (risk) distance is normalized to make similar the impact of each variable on the risk-return distance measure. The Euclidean distance is used to measure the risk-return distance. The cross-market average risk-return distance for 14 emerging markets is calculated. For each semi-annual period, the correlation between weekly returns for each emerging market and those for each developed market is calculated. Then, the average correlation of all the bilateral correlations is computed. U.S dollar stock market index returns are used to compute the distances and parameters.