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Are International Portfolio Diversification Opportunities Decreasing? Evidence from Principal Component Analysis

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ABSTRACT

I use principal component analysis to create an index of portfolio diversification- a quantifiable measure of diversification opportunities offered to US investors by financial markets abroad. The index is estimated for three market clusters: Developed, emerging, and world (emerging and developed combined). During the period under study, the portfolio diversification indices for all three clusters display considerable dynamics. This is suggestive of highly variable benefits from investing abroad. In addition, I find that while the diversification opportunities offered by all three market clusters on average decrease between 1995 and 2014, after 2012 they either level off or begin to increase. Furthermore, my study finds that the homogeneity of international markets as well as their vulnerability to common shocks increase simultaneously, regardless of the type of market. Therefore, international diversification is unlikely to provide protection against global shocks. Finally, I find that the level of diversification opportunities is expected to increase, however, decreases are not unlikely.

Keywords: International Portfolio Diversification, Index of Portfolio Diversification, Principal Component Analysis, Developed Markets, Emerging Markets, International Financial Markets
JEL Classifications: F01, F30, F36, G1

1. INTRODUCTION

The scope for international portfolio diversification relies on the nature of relationship between national markets. Studies as early as Solnik (1974) develop the thesis that domestic and foreign national markets are likely to follow divergent paths and thus provide benefits from diversifying abroad.

International portfolio diversification theory is largely based on national market return correlations. The underlying assumption is that in the presence of low correlation between foreign and domestic market returns, the scope for benefits from diversification increases. Therefore, an investor could increase the expected return per unit of risk by incorporating foreign assets in their domestic portfolio.

Correlations between market returns are also at the heart of the closely related theory of financial integration. The underlying assumption here is that the more financially integrated a stock market is, the more correlated its returns are expected to be with foreign markets. Consequently, the smaller the potential gain from diversification.

Literature suggests that market return correlations are increasing in the recent years. Quinn and Voth (2008), for instance, report that since the 1990s national stock market correlations are at historic high. Goetzmann et al. (2005) further claim that historic stock market correlations exhibit U-shape. According to these two studies, increasing correlations imply increasing integration, and hence decreasing gains from portfolio diversification.

Literature, however, identifies numerous potential deficiencies of correlations as measures of financial integration and portfolio diversification benefits. Wilcox (2005), for instance, claim that outliers and heavy-tailed distributions may alter the robustness of sample correlations. Boyer et al. (1999) add that conditional heteroscedasticity and high volatility may demean the reliability of conclusions based on sample integration; Forbes and Rigobon (2002) report that correlation estimates of national market returns are biased upward when volatility in one market increases market volatility elsewhere; and Carrieri et al. (2007) and Huber and Ronchetti (2009) explain that correlations between country national returns are not adequate measures of either diversification benefits, or financial integration. In a similar manner, Obstfeld and

Taylor (2003) further recognize that higher correlation between market returns might be a result of common shocks among a group of countries and do not necessarily imply integration. Longin and Solnik (2001) also contribute by suggesting that correlations of market returns are mainly affected by trends and increase only when asset prices fall, nut not when asset prices increase.

Some studies of financial integration avoid the use of correlations by utilizing principal component analysis (PCA). Analyses by Pukthuanthong and Roll (2009) and Berger et al. (2011) use PCA to develop a new indicator of integration. They find that simple correlations among country indices may not reflect properly the level of integration and that PCA better captures potential benefit from portfolio diversification. Volosovych (2011) uses PCA to create an index of integration and finds that the level of integration by the end of the 20th century was higher than any previous period in history.

Literature is not unanimous on the benefit of international diversification either. Bekaert et al (2009), for instance, do find benefits from international diversification. Rua and Nunes (2009) confirm their results in the short run, but not in the long run, while You and Daigler (2010) detect no substantial benefits altogether. Furthermore, Baele and Inghelbrecht (2009) and Lucey and Zhang (2010) suggest that scope for diversification benefits still exist, but is determined by individual countries' geographical and cultural differences.

This study addresses the ambiguities in international portfolio diversification literature by using national market returns to explore the evolution of diversification opportunities available to US investors abroad. The analysis is based on a PCA, PCA, and thus overcomes the deficiencies inherent to correlations.

More broadly, the PCA is a non-parametric method used to describe the common features of sample data. It is robust to the presence of outliers and heavy-tailed distributions (Stevens, 1996) and therefore particularly useful in the analysis of market returns. The technique transforms the observed variables into new variables, called PC, where the goal is several components to account for most observed data variability. In many cases, most of the observed data variation is summarized in the first PC.

Studies often assign meaning to the first component. Meric et al. (2011) and Meric et al. (2012), for instance, analyze national market returns and refer to the first component as an indicator of common sources of variability. Volosovych (2011), in a similar manner, uses the fraction of total variation accounted for by the first component to reflect the extent of market integration.

Similarly to Meric et al. (2011), Meric et al. (2012) and Volosovych (2011), I refer to the first component as a factor causing common variability, where the amount of common variability is measured by the proportion of total variability explained by the first component. The greater the proportion of total variation accounted for by the first component, the greater the extent of common variability, the lower the scope for portfolio diversification. Correspondingly, the less the proportion of total variation accounted for by the first component, the lower the extent of common variability, the greater the scope for portfolio diversification.

In this study, I analyze national market returns and frame the fraction of data variability explained by the first component into an index of portfolio diversification. My index is similar in nature to the index of integration developed by Volosovych (2011). It takes values between zero and one and quantifies the level of diversification opportunities offered to US investors abroad at a point of time. In my analysis, I consider three market clusters.

The first cluster, the World markets cluster, contains 43 developed and emerging markets along with the US. The goal of exploring this cluster is to learn more about the common variability of US returns with foreign markets and thus gain insight on the diversification opportunities offered to US investors abroad.

The second cluster, the developed markets cluster, contains 22 developed markets along with the US. The goal of exploring this cluster is to learn more about the common variability of US returns with other developed markets and thus gain insight on the diversification opportunities offered to US investors by developed markets.

The third cluster, the emerging markets cluster contains 21 emerging markets along with the US. The goal of exploring this cluster is to learn more about the common variability of US returns with emerging markets and thus gain insight on the diversification opportunities offered to US investors by emerging markets.

I create a separate index of portfolio diversification for each cluster and then analyze each index by setting up log-linear and quadratic deterministic trend models. The construction of trend models allows for an insight on the rate of change of each index as well as for the construction of point and interval forecasts of future levels of diversification opportunities.

The reminder of this paper is organized as follows. The following section briefly describes data and outlines methodology relevant to PCA and trend models. In section 3 I present the results from the PCA, and in section 4 I offer the results from the estimation of the trend models. Section 5 concludes.

2. DATA AND METHODOLOGY

In this section, I describe the data and techniques utilized in this paper. Subsection 2.1 describes the emerging and developed country returns; subsection 2.2 describes the PCA while subsection 2.3 discusses relevant PCA literature. Subsection 2.4 describes the construction of the index of portfolio diversification and finally subsection 2.5 describes the construction of the trend models used in the analysis of the portfolio diversification indices.

2.1. Data

In this subsection, I describe the data used in my analysis.

My study is motivated by the desire to explore potential gains from diversification for US investors from investing abroad. Therefore, I use monthly prices of the MSCI Bara indices for the US and 43 foreign markets. More specifically, I analyze the national market returns for the US, 22 developed, and 21 emerging stock markets for the period between January 1995 and December 2014. The indices are denominated in US dollars and thus are particularly useful for cross-country analysis from the prospective of an US investor.

Market returns for each country are calculated as follows:

$$R_{it} = \ln\left(\frac{P_{it}}{P_{i(t-1)}}\right)$$

Where, P_{it} is each country's monthly index price at time t.

I choose monthly data since it implicitly accounts for differences in trading days and is less affected by random noise. The choice of countries is based on the MSCI classification as of May 2015. Qatar is also classified as an emerging market, but is not included here due to lack of data for a sufficiently long period.

MSCI indices are established consistently across countries and thus provide an adequate ground for exploration of cross-market relations. They are value weighted and calculated with dividends reinvested. To avoid double counting, stock prices of companies set up abroad are not included. All indices are in US dollars, which provides additional comparability across markets and implicitly takes care of currency market effects.

Descriptive statistics for all markets are reported in Table 1. For each country returns, the table provides the mean and standard deviation, the max and min values, as well as the return-to-risk (Sharpe) ratio.

The highest mean returns over the period of study are offered by Egypt, 0.89%, while Russia is the riskiest with a standard deviation of 15.67%. The lowest mean return is observed in Greece, −0.46%, while the US seems to be the safest with a standard deviation of only 0.44%.

The minimum returns range from −93% for Russia to −16% for Japan, while the maximum returns range from 10.28% for the US to 54.4% for Turkey.

The last column of Table 1 provides the mean-to-standard deviation (Sharpe ratio) for all markets. The highest value is 0.6277 for the UK and the lowest is −0.124 for Thailand (0.1418 for the US). Further comparison of individual country mean-to-standard deviation ratios with the US shows a relatively high return-to-standard deviation benefit for Denmark and UK. Therefore, for US investors, diversification benefits from investing in these markets may be worthwhile if one assumes a normal distribution for returns.

In the next subsection, I provide a brief introduction to the details of the PCA and in subsection 2.3 I offer a brief review of relevant literature utilizing PCA.

2.2. PCA

In this subsection, I introduce the PCA.

PCA is a completely non-parametric statistical technique that is used to decrease dimensionality and identify patterns in data (Smith, 2002; Pearson, 1901; Hotelling, 1933; Rencher and Christensen, 2012). Its objective is to derive linear combinations of uncorrelated, optimally-weighted observed variables, called PCs, such that each PC explains the maximum amount of variation remaining in the data subject to it being uncorrelated with all previous PCs and subject to the restriction that,

$$\sum_{i=1}^{n} \alpha_{ik}^{2} = 1$$

Where n is the number of variables and α_{ik} is the loading (or weight) on variable i in PC number k.

PCs are constructed using the correlation matrix of the original variables. The eigenvectors of the correlation matrix provide the weights for the observed variables and the eigenvalues measure the variance accounted for by the PCs. The number of components derived equals the number of observed variables. A key feature of PCs is that they are uncorrelated to each other and together explain the total variance of all variables (Shlens, 2009; Stevens, 1996).

The PCs are ranked by their variance. The first component is the one with the largest variance. It accounts for the greatest possible fraction of the total variation in the dataset. Each remaining component is constructed such that it accounts for the maximum possible fraction of the total variation that remains unexplained by all previous components. Consequently, each successive component accounts for a progressively smaller amount of the total data variation. In practice, only the first few components, and often only the first one, are kept for further analysis (Flury 1997; Marida 1979; Rencher and Christensen, 2012). Appendix A offers further technical details on PCA and comprehensive analysis is available in Jolliffe (2002) and Jackson (2003) among others. The results from the PCA are reported in section 3.1.

Next, I proceed with a review of relevant literature utilizing PCA.

2.3. Relevant Literature

In this subsection, I briefly review literature that utilizes PCA in the analysis of portfolio diversification benefits and financial integration.

A considerable body of literature utilizes PCA in the analysis of portfolio diversification and financial market integration. Meric et al. (2012) use PCA to find that the diversification opportunities among Asian countries decreased between 2001 and 2011. Meric et al. (2011) further use PCA to show that global diversification opportunities decreased between 2001 and 2010. These studies look at the number of significant PCs in each period, arguing that a low or decreasing number of components implies high or increasing market integration and thus low and decreasing portfolio diversification opportunities. Bordo and Murshid (2006) use PCA in the analysis of bond spreads and find a considerable

Table 1: Descriptive statistics of national market returns. The table provides mean, standard deviation, min, max, and mean - to standard deviation (Sharpe) ratio for each national market and the US. The statistics are based on 240 monthly observations of returns for the period between January 1995 and December 2014

Variable	Observed	Mean±SD	Minimum	Maximum	Sharpe ratio
Egypt	240	0.0089±0.00926	−0.3948	0.3507	0.0961
Greece	240	−0.0046±0.1032	−0.4577	0.2599	−0.0445
Hungary	240	0.0049±0.1113	−0.5682	0.3795	0.044
India	240	0.0051±0.0878	−0.3362	0.3121	0.058
Indonesia	240	0.0023±0.1300	−0.5247	0.4420	0.0176
Korea	240	0.0031±0.1086	−0.3747	0.5340	0.0285
Malaysia	240	0.0011±0.0823	−0.3611	0.4051	0.0133
Mexico	240	0.0070±0.0834	−0.4195	0.1741	0.0839
Peru	240	0.0078±0.0888	−0.4469	0.3043	0.0878
Philippines	240	−0.0002±0.0868	−0.3465	0.3601	−0.0023
Poland	240	0.0027±0.1046	−0.4298	0.3393	0.0258
Russia	240	0.0058±0.1567	−0.9307	0.4770	0.036
South Africa	240	0.0038±0.0808	−0.2467	0.2564	0.047
Thailand	240	−0.0014±0.1126	−0.4163	0.3589	−0.124
Turkey	240	0.0065±0.1470	−0.5317	0.5440	0.0442
Brazil	240	0.0038±0.1104	−0.4943	0.3111	0.0344
Chile	240	0.0020±0.0686	−0.3440	0.1828	0.0291
China	240	−0.0002±0.0981	−0.3241	0.3819	−0.002
Colombia	240	0.0069±0.0912	−0.3361	0.2648	0.0756
Czech Republic	240	0.0050±0.0838	−0.3487	0.2629	0.0596
USA	240	0.0063±0.0444	−0.1893	0.1028	0.1418
Australia	240	0.0044±0.0623	−0.2952	0.1569	0.0706
Austria	240	−0.0002±0.0782	−0.4673	0.2203	−0.0025
Belgium	240	0.0031±0.0654	−0.4550	0.1616	0.0474
Canada	240	0.0067±0.0604	−0.3168	0.1906	0.1109
Denmark	240	0.0086±0.0590	−0.2966	0.1679	0.1457
Finland	240	0.0056±0.0950	−0.3823	0.2804	0.0589
France	240	0.0039±0.0609	−0.2540	0.1423	0.064
Germany	240	0.0042±0.689	−0.2790	0.2020	0.0609
Hong Kong	240	0.0036±0.0727	−0.3441	0.2837	0.0495
Ireland	240	−0.0001±0.0665	−0.3046	0.1757	−0.0015
Israel	240	0.0047±0.0670	−0.2094	0.2386	0.0701
Italy	240	0.0009±0.0712	−0.2695	0.1786	0.01264
Japan	240	−0.0010±0.0526	−0.1600	0.1543	−0.019
Netherlands	240	0.0039±0.0607	−0.2899	0.1339	0.06425
New Zealand	240	0.0013±0.0637	−0.2562	0.1447	0.0204
Norway	240	0.0035±0.0801	−0.4058	0.1696	0.0436
Portugal	240	−0.0006±0.0677	−0.3045	0.1511	−0.0088
Singapore	240	0.0019±0.0751	−0.3450	0.2284	0.0253
Sweden	240	0.0070±0.0753	−0.3100	0.2054	0.0929
Spain	240	0.0055±0.0724	−0.2945	0.1940	0.0759
Switzerland	240	0.0063±0.0487	−0.1710	0.1347	0.1293
UK	240	0.0029±0.0462	−0.2122	0.1243	0.6277

SD: Standard deviation

dissimilarity in the patterns of emerging and advanced countries in the 1990s. In a similar fashion, they suggest that the existence of more than one strong component, where each component is related only to a subset of countries, would imply market segmentation. In a similar manner, Berger et al. (2011) perform PCA and find that frontier markets exhibit low levels of integration with no indication of increasing integration over time. This suggests the existence of potential diversification opportunities in those markets. Pukthuanthong and Roll (2009), on the other hand, find increasing global market integration and thus decreasing portfolio diversification opportunities. These two studies take PCs to represent global factors and use them as independent variables in the regressions of country returns. The resulting adjusted R-square from those regressions is their suggested measure of market integration.

Volosovich (2011) applies PCA on various country bond yields and uses the fraction of total variance explained by the first components to create an index of market integration. He finds that market integration in the end of 20th century is higher than any time in the past.

Overall, the literature is inconclusive on the evolution of financial integration and the significance of the diversification benefits available to US investors. In the following subsection, I present details on the construction of the index of portfolio diversification and how it quantifies the benefits available from investing abroad.

2.4. Index of Portfolio Diversification

My study builds upon existing literature by introducing an index of portfolio diversification: A method based on PCs designed to measure the evolution of portfolio diversification opportunities over time. My approach differs from previous studies in numerous aspects.

In this article, I explore the national market financial returns for a large set of countries, both emerging and developed, over a period of 20 years, between 1995 and 2015.

I separate the markets into three clusters. The first cluster contains 43 developed and emerging markets along with the US; the second contains 22 developed markets along with the US, and the third cluster contains 21 emerging markets along with the US.

For each cluster, I estimate the PCs for each year and obtain the proportion of the total variation of returns explained by the first PC. This value is then subtracted from one to construct a dynamic measure of diversification and represents my index of portfolio diversification. The three indices, one for each cluster, can be plotted together over time to provide a graphic illustration of the evolution of portfolio diversification opportunities offered by the international stock markets as a whole, as well as by developed and emerging markets separately. More technical details on the construction of the indices of portfolio diversification are offered in Appendix B and the results are discussed in section 3.2.

The following subsection offers details on the construction of trend models used in the analysis of portfolio diversification indices.

2.5. Trend Models

In this part, I describe my trend models.

First, I begin by constructing a deterministic log-linear trend model for each index. Doing this allows me to obtain the average rate of change of an index per year. The technical details on the deterministic log-linear trend model are offered in Appendix C and the results are discussed in section 4.1.

Next, I continue with the construction of a quadratic deterministic trend model for each index. Doing this allows me to obtain an improved prospect on the evolution of an index. The technical details on the quadratic deterministic trend model are offered in Appendix D and the results are discussed in section 3.3.

Finally, I describe the use of quadratic deterministic trend models in the construction of 5-year point and interval forecasts for each index. Doing this provides an insight on the level of diversification opportunities offered to US investors in the future. The technical details on the forecast construction are presented in Appendix E and the results are discussed in subsection 4.3.

The next section presents the results from the PCA I perform on market returns.

3. RESULTS FROM PCA

In this section, I describe the results from the PCA. Subsection 3.1 discusses the fraction of total variation explained by the first PC for all three clusters of markets. Subsection 3.2 looks at the number of PCs with eigenvalues above 1 in every period. Subsection 3.3 describes the three indices of portfolio diversification.

3.1. Fraction of Total Variance Explained by the First PC

In this subsection, I describe the variation explained by the first component for all three clusters.

First I begin by describing the world markets cluster, comprised of 44 developed and emerging markets including the US, and then proceed with the developed and emerging market clusters.

The fraction of the variation explained by the first component when the world markets are considered as a whole is described in the second column of Table 2. The largest fraction explained by the first component is recorded in 2008 and equals 0.81. This means, that in 2008, 81% of the total variation of returns of all 44 national markets under study was due to a single underlying common factor. This suggests a very strong relationship among markets and therefore little opportunity for diversification offered to investors.

The correlation of individual country returns with the first PC is described in Table 3.

The 15th column of Table 3 indicates that in 2008, for all but three countries the correlation values are above 0.8. This implies that the returns in these countries were highly associated with this common factor. The three countries that are not as associated are Ireland, with a correlation coefficient of 0.72; Turkey, with a correlation coefficient of 0.75; and the Philippines, with a correlation coefficient of 0.66. For the US, the correlation coefficient is 0.91, suggesting the US is one of the countries most associated with the common component.

The smallest fraction of variation explained by the first component is recorded in 1996 and equals 0.27. This means, that in 1996, 27% of the total variation of returns of all 44 national markets under study was due to a single underlying common factor. This suggests a relatively weaker integration among markets and therefore a potential for diversification offered to investors. The third column of Table 3 indicates that in 1996, for 27 countries the correlation values were below 0.5. This implies that the returns in these countries were not highly associated with this common component. Some countries, like New Zealand, Switzerland, Egypt, India, Chile, and Czech Republic exhibited even negative correlations, implying they would offer excellent diversification opportunities. For the US, the correlation coefficient is 0.78, again suggesting the US is one of the countries most associated with the common component.

Next, I proceed with analyzing the developed markets cluster, comprised of the US and 22 developed markets.

The fraction of the variation explained by the first component when developed markets are considered along with the US is described in the 5th column of Table 2. The largest fraction of variation explained by the first component is recorded again in 2008 and

Table 2: Estimates from principal component analysis

Date	World variance	World index	World component	DM variance	DM index	DM component	EM variance	EM index	EM component
1995	0.3383	0.6617	10	0.4051	0.5949	5	0.3531	0.6469	6
1996	0.2718	0.7282	10	0.3434	0.6566	6	0.3309	0.6691	7
1997	0.4623	0.5377	10	0.5993	0.4007	5	0.4564	0.5436	5
1998	0.5884	0.4116	8	0.6673	0.3327	3	0.5889	0.4111	5
1999	0.3761	0.6239	10	0.4863	0.5137	5	0.3856	0.6144	6
2000	0.3186	0.6814	9	0.4293	0.5707	7	0.2621	0.7379	6
2001	0.5873	0.4127	7	0.6912	0.3088	4	0.5683	0.4317	4
2002	0.5135	0.4865	7	0.6859	0.3141	4	0.4167	0.5833	6
2003	0.4544	0.5456	9	0.5829	0.4171	5	0.3723	0.6277	7
2004	0.4887	0.5113	9	0.6299	0.3701	4	0.4177	0.5823	6
2005	0.5936	0.4064	8	0.6327	0.3673	5	0.5872	0.4128	5
2006	0.6587	0.3413	8	0.7208	0.2792	3	0.6466	0.3534	5
2007	0.5527	0.4473	9	0.63	0.37	5	0.5375	0.4624	4
2008	0.8131	0.1869	4	0.8689	0.1311	1	0.7747	0.2253	3
2009	0.7256	0.2744	5	0.7797	0.2203	3	0.6729	0.3271	3
2010	0.7415	0.2585	5	0.8291	0.1709	2	0.6665	0.3335	4
2011	0.6837	0.3163	6	0.7682	0.2318	3	0.6565	0.3435	4
2012	0.7217	0.2783	5	0.7835	0.2165	2	0.7119	0.2881	4
2013	0.5319	0.4681	8	0.6631	0.3369	4	0.462	0.538	6
2014	0.4717	0.5283	9	0.553	0.447	5	0.4803	0.5197	5

Estimated yearly values of the fraction of total variance in national market returns explained by the first principal component, from 1995 to 2014. Developed markets (DM) include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Emerging markets (EM) include: Egypt, Greece, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey, Brazil, Chile, China, Colombia, Czech Republic. World Markets include all markets classified as emerging and developed

equals 0.86. This means, that in 2008, 86% of the total variation of returns of all 23 markets in this cluster was due to a single underlying common factor. This suggests a very strong integration among developed markets and therefore little opportunity for diversification offered to investors.

The correlation of individual country returns with the first PC is described in Table 4.

The 15th column of Table 4 indicates that in 2008 for all but one country, the correlation values are above 0.8. This implies that the returns in these countries were highly associated with this common component. The only country that is relatively less associated is Ireland, with a correlation coefficient of 0.77. For the US, the correlation coefficient is 0.92, again suggesting the US is one of the countries most associated with the common component.

The smallest fraction of variation explained by the first component is recorded in 1996 and equals 0.34. This means, that in 1996, 34% of the total variation of returns of all 23 markets in this cluster was due to a single underlying common factor. This suggests a relatively weaker integration among markets and therefore a potential for diversification offered to investors. The third column of Table 4 indicates that in 1996 for 7 countries, the correlation values are below 0.5. This implies that the returns in these countries were relatively less associated with this common component. Some countries, like New Zealand, Portugal, and Switzerland, exhibited even negative correlations, implying they would offer excellent diversification opportunities. For the US, the correlation coefficient is 0.86, again suggesting the US is one of the countries most associated with the common component.

Finally, I describe the cluster comprised of the US and 21 emerging markets.

The fraction of the variation explained by the first component when only emerging markets are considered, along with the US, is described in the eight column of Table 2. The largest fraction of variation explained by the first component is recorded in 2008 and equals 0.77. This means, that in 2008, 77% of the total variation of returns of all 21 emerging markets under study and the US was due to a single underlying common factor. This suggests a relatively strong relationship among markets and therefore little opportunity for diversification offered to investors.

The correlation of individual country returns with the first PC is described in Table 5.

The 15th column of Table 5 indicates that in 2008 for all but one country, The Philippines, the correlation values are above 0.8. This implies that the returns in these countries were highly associated with this common component. For the US, the correlation coefficient is 0.89, suggesting the US is one of the countries most associated with the common component.

The smallest fraction of variation explained by the first component is recorded in 2000 and equals 0.26. This means, that in 2000, 26% of the total variance of returns of all 21 emerging markets and the US was due to a single underlying common factor. This suggests a relatively weaker relationship among markets and therefore a potential for diversification offered to investors. The 9th column of Table 5 indicates that in 2000, for 7 countries the correlation values are below 0.5. This implies that the returns in these countries were not highly associated with this common component. One country, Egypt, exhibited negative correlations, implying it would offer excellent diversification opportunities. For the US, the correlation coefficient is 0.85, again suggesting the US is one of the countries most associated with the common component.

Table 3: Estimated correlations of national market returns with the first component for the countries in the World Cluster, correlations are derived by multiplying individual country loadings in the first component by the first component's eigenvalue

Date	1995	1996	1997	1998	1999	2000	2001	2002
Australia	0.5381157	0.7538861	0.8145561	0.8003773	0.7770062	0.6495646	0.9180753	0.8837056
Austria	0.8443981	0.5674895	0.5737073	0.7520392	0.649268	0.6656633	0.3899024	0.5482775
Belgium	0.7282885	0.4395364	0.797868	0.7138775	0.3714171	0.6312196	0.5047889	0.9098366
Canada	0.7109299	0.6480654	0.829891	0.9341975	0.818094	0.7551423	0.8774075	0.9473704
Denmark	0.6596257	0.2071458	0.8073396	0.66096	0.5280388	0.6866291	0.8311479	0.8342941
Finland	0.2538209	0.2787304	0.8262828	0.8695771	0.7074418	0.3590389	0.4153198	0.5525535
France	0.587877	0.5806306	0.797868	0.8370125	0.7123235	0.858848	0.8809659	0.945945
Germany	0.7228881	0.4353865	0.7703553	0.8334507	0.8262302	0.7090925	0.9389175	0.9549721
Hong Kong	0.7286743	0.8489864	0.8876225	0.4874516	0.8416889	0.8288969	0.8697823	0.7126658
Ireland	0.5732186	0.6404574	0.5416843	0.8614359	0.5373954	0.402468	0.8596153	0.8262172
Israel	0.0443608	0.6390741	0.8123009	0.555125	0.5976032	0.5836722	0.9201087	0.3078716
Italy	0.1195813	0.6881804	0.6057302	0.738301	0.5378022	0.5582138	0.8636821	0.9421441
Japan	0.4709959	0.2552147	0.5277024	0.6456953	0.5495997	0.5196517	0.6567847	0.4399523
Netherlands	0.7136302	0.4931383	0.8501872	0.8293801	0.7334776	0.8083055	0.9312923	0.9687503
New Zealand	0.2877665	−0.3433986	0.7929067	0.8644889	0.7273755	0.436163	0.7762464	0.5573046
Norway	0.4243206	0.4627062	0.5633336	0.8914564	0.4963076	0.8273993	0.9145168	0.9326419
Portugal	0.8328257	0.2147538	0.8555996	0.7535656	0.1082113	0.6390817	0.4834383	0.9335922
Singapore	0.8146956	0.866969	0.7193892	0.7428804	0.8396549	0.3264671	0.8306395	0.5696575
Spain	0.6006066	0.4578648	0.6012199	0.9581121	0.4531858	0.8397542	0.8794409	0.9307415
Sweden	0.3938467	0.2714682	0.7902006	0.8415919	0.8225689	0.5050505	0.9470511	0.8461718
Swiss	0.627223	−0.2427652	0.7820821	0.8405742	0.4369134	0.5900368	0.8174225	0.8466469
UK	0.7228881	0.3437444	0.6914255	0.8395566	0.8185008	0.6783926	0.8530068	0.9521215
USA	0.5138137	0.7881222	0.7356262	0.9082476	0.8160599	0.5964014	0.8926579	0.9307415
Egypt	−0.2279759	−0.1334863	0.16237	0.4828722	0.288428	−0.2336186	0.5337647	−0.0612893
Greece	0.8559704	0.0919879	0.7211933	0.7047187	−0.4637629	0.3055013	0.6867772	0.533074
Hungary	0.7406324	0.7400533	0.6233203	0.9408122	0.3559583	0.5773076	0.740662	0.5919877
India	0.4424507	−0.1632267	0.552509	0.469134	−0.2217112	0.4125765	0.8596153	0.451355
Indonesia	0.5905772	0.9326747	0.6688741	0.6314483	0.5154277	0.4125765	0.3055167	0.2503832
Korea	0.4914404	0.1469732	0.4853058	0.4213048	0.544718	0.4522617	0.9404425	0.7164667
Malaysia	0.8008088	0.6145209	0.7987701	0.7393186	0.3388723	−0.2059139	0.4534458	0.4855629
Mexico	0.315926	0.6788433	0.8767979	0.8288713	0.7253414	0.7367972	0.8763908	0.7715795
Peru	0.5855625	0.0850716	0.5353699	0.7815509	0.384435	0.3260927	0.0757438	0.7288195
Philippines	0.7618484	0.7144627	0.586336	0.8054655	0.766836	0.3609108	0.5881579	−0.1173523
Poland	0.4756249	0.5996507	0.2836964	0.8522771	0.6480476	0.6166184	0.6359425	0.6998378
Russia	0.3710877	0.3510066	0.6851111	0.8965447	0.6708289	0.4095814	0.8143724	0.6119423
South Africa	0.6002208	0.7113503	0.6210652	0.7764626	0.8917265	0.7600093	0.7482873	0.6428245
Taiwan	0.6295375	0.1746388	0.4920712	0.7052275	0.5825513	0.0003744	0.7213449	0.8480723
Thailand	0.7151731	0.7213791	0.8389116	0.586672	0.7985671	0.1639823	0.6938941	0.5397255
Turkey	0.5454449	0.5757892	0.4135924	0.7011569	0.5068847	−0.0524144	0.8911329	0.4608572
Brazil	0.1384828	0.5093919	0.911076	0.8558389	0.5622108	0.9505733	0.9170586	0.8133892
Chile	0.5284721	−0.2410361	0.7902006	0.8568565	0.7029669	0.0666412	0.8469066	0.769679
China	0.6229798	0.5636855	0.1317001	0.5729338	0.3921644	0.1827018	0.6247589	0.7102902
Colombia	−0.119967	0.0280114	0.2295731	0.5612309	0.2953437	−0.5129127	0.5764659	0.4014684
Czech	0.369159	−0.0376943	0.0342781	0.8772094	−0.010577	0.434291	0.7975969	0.1615376

Date	2003	2004	2005	2006	2007	2008	2009
Australia	0.7574851	0.8648192	0.8927136	0.8737606	0.9069086	0.9683637	0.8830482
Austria	0.649273	0.7539925	0.8600097	0.9232898	0.801867	0.9587937	0.8887015
Belgium	0.9220392	0.81242	0.8308828	0.907139	0.8960592	0.9480274	0.9062268
Canada	0.6850456	0.722924	0.8416138	0.7800857	0.8704153	0.8971869	0.9034002
Denmark	0.7261841	0.8045369	0.771607	0.8048503	0.860059	0.9390556	0.855347
Finland	0.7302085	0.8068555	0.8155529	0.780624	0.6869623	0.859505	0.9067921
France	0.9739094	0.8819765	0.9172415	0.8543795	0.8294835	0.9767374	0.9565413
Germany	0.9193562	0.8369966	0.8830046	0.9615135	0.8127163	0.9552049	0.9582373
Hong Kong	0.25801	0.6389924	0.7358372	0.9275967	0.7560037	0.9354668	0.7581099
Ireland	0.7176881	0.7433272	0.7210182	0.7192508	0.5266875	0.7279176	0.7875071
Israel	0.4444747	0.6107061	0.2953569	0.7025616	0.8398398	0.8726637	0.368031
Italy	0.7042734	0.8119563	0.8503007	0.8629933	0.7234556	0.9863074	0.9638907
Japan	0.3434171	0.3111494	0.6663414	0.9432092	0.2431245	0.9295	0.8920935
Netherlands	0.9609419	0.8337506	0.8457018	0.8263848	0.8521686	0.9623824	0.9486267

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Table 3: (*Continued*)

Date	2003	2004	2005	2006	2007	2008	2009
New Zealand	0.4462634	0.7090126	0.7102873	0.7117138	0.708661	0.926495	0.8581736
Norway	0.9090716	0.8068555	0.8278168	0.773087	0.8620317	0.9205137	0.8095551
Portugal	0.6273622	0.858791	0.5702738	0.6379583	0.5607151	0.9181212	0.9050961
Singapore	0.5021581	0.6232263	0.5656748	0.901217	0.917758	0.9737468	0.9282748
Spain	0.8232173	0.8573999	0.8850486	0.8236929	0.705209	0.9348687	0.947496
Sweden	0.8956569	0.8884684	0.9054885	0.7892378	0.7969354	0.9659712	0.8604349
Swiss	0.8893966	0.8101014	0.7618981	0.908754	0.6371538	0.888215	0.9322321
UK	0.9247221	0.8309684	0.8860706	0.8559946	0.9192374	0.9372612	0.9554107
USA	0.9314295	0.8522991	0.7159083	0.8721455	0.747127	0.9139343	0.9384507
Egypt	0.5974027	0.1043348	0.0475228	0.741862	0.4393994	0.9276912	0.7711125
Greece	0.7700055	0.6403836	0.8548997	0.8608399	0.7540311	0.9420462	0.848563
Hungary	0.5553699	0.6464118	0.7997119	0.8161559	0.6179209	0.926495	0.9446694
India	0.3228479	0.4873593	0.8206629	0.8075421	0.8097574	0.86429	0.8593043
Indonesia	0.6640292	0.4442342	0.3367477	0.9135993	0.7816477	0.8846262	0.9056615
Korea	0.7217125	0.6978836	0.8416138	0.850611	0.7002774	0.8774487	0.8491283
Malaysia	0.2660588	0.6575408	0.4874921	0.7020233	0.7328255	0.849935	0.7377579
Mexico	0.7624039	0.8082466	0.8497897	0.8834511	0.6016468	0.8959906	0.9418427
Peru	0.4462634	0.1585888	0.8329268	0.7332482	0.8097574	0.8337856	0.734366
Philippines	0.3103274	0.0802218	0.2222841	0.2745643	0.7111268	0.6621239	0.7315393
Poland	0.6412241	0.8481257	0.9494344	0.6934095	0.8546344	0.878645	0.8412137
Russia	0.43106	0.3000204	0.8390588	0.805927	0.3126591	0.8385706	0.8123817
South Africa	0.5410608	0.7233877	0.9397254	0.9125226	0.8408261	0.9528124	0.9073575
Taiwan	0.1377246	0.7261699	0.7148863	0.6917944	0.6258113	0.8618975	0.7869418
Thailand	0.4185396	0.6742344	0.785404	0.7176357	0.5015367	0.8983831	0.7615019
Turkey	0.6300452	0.4711294	0.776717	0.800005	0.7934834	0.7566276	0.8926589
Brazil	0.7185824	0.6389924	0.7992009	0.8382287	0.8975387	0.9133362	0.7931605
Chile	0.7226068	0.6403836	0.7378812	0.79839	0.7574832	0.869075	0.3035832
China	0.450735	0.6895368	0.9325714	0.8484576	0.6909075	0.8242157	0.7948565
Colombia	0.7874447	0.4344963	0.6740064	0.7520909	0.5000573	0.9175231	0.8440403
Czech	0.4806945	0.8175208	0.8058439	0.7854693	0.8077848	0.8995794	0.8909629

Date	2010	2011	2012	2013	2014
Australia	0.9750497	0.9598459	0.8892069	0.7614322	0.613212
Austria	0.9681952	0.9192581	0.9613352	0.7609484	0.7116174
Belgium	0.9127882	0.8704431	0.8069355	0.8315768	0.880638
Canada	0.8379601	0.8912855	0.9382316	0.8630209	0.8241459
Denmark	0.9224987	0.7996887	0.8565237	0.7430494	0.6177678
Finland	0.9116458	0.8095614	0.9072389	0.8872088	0.846925
France	0.981333	0.9258399	0.9016039	0.9191367	0.8783601
Germany	0.9607695	0.8786703	0.9748592	0.8693098	0.8123008
Hong Kong	0.7745562	0.9159672	0.9106199	0.9467108	0.5580867
Ireland	0.8539539	0.7859767	0.7156481	0.6192079	0.4952165
Israel	0.7385702	0.8797673	0.6339402	0.2960588	0.2933941
Italy	0.9561999	0.8534401	0.8525792	0.8223854	0.6742598
Japan	0.7991181	0.2720477	0.9032944	0.4460232	0.2965832
Netherlands	0.9630544	0.9313248	0.8785003	0.7967464	0.7890662
New Zealand	0.9196427	0.6899921	0.8441267	0.7773961	0.4400912
Norway	0.9739073	0.9455853	0.8886433	0.9007539	0.6961277
Portugal	0.8887975	0.8622158	0.7979195	0.6820962	0.7694762
Singapore	0.8990792	0.9082884	0.8880798	0.8601184	0.6350798
Spain	0.9185002	0.7612949	0.7314262	0.9249417	0.8492029
Sweden	0.934494	0.9631368	0.9365411	0.8083565	0.8715264

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Table 3: (*Continued*)

Date	2010	2011	2012	2013	2014
Swiss	0.8311056	0.9022551	0.9072389	0.8828549	0.1934
UK	0.9864738	0.9220005	0.9455571	0.9215554	0.8305241
USA	0.9059337	0.9335187	0.8993499	0.7328905	0.8177678
Egypt	0.5609249	0.312087	0.5804075	0.6888687	−0.005467
Greece	0.8568099	0.6614709	0.7477677	0.8523783	0.7726653
Hungary	0.9190714	0.9028036	0.9106199	0.4847236	0.306606
India	0.8522403	0.6225286	0.8215866	0.771591	0.6523919
Indonesia	0.812827	0.7355162	0.7855224	0.2689684	0.388155
Korea	0.9236411	0.8929309	0.9201995	0.4798861	0.75672
Malaysia	0.8259648	0.9214521	0.7883399	0.1881811	3.6947615
Mexico	0.8413873	0.9181612	0.8773733	0.7033814	0.4564921
Peru	0.5569265	0.4590806	0.696489	0.3884562	0.6651482
Philippines	0.7340005	0.7064466	0.7776334	0.6608109	0.7644648
Poland	0.9539151	0.9686216	0.1634	0.632753	0.8086562
Russia	0.8636644	0.8803158	0.9866928	0.8586671	0.5662871
South Africa	0.9396349	0.7069951	0.8807543	0.6042114	0.8054671
Taiwan	0.8973656	0.7991403	0.6446468	0.6375906	0.7302963
Thailand	0.6740238	0.8095614	0.9078024	0.6825799	0.6505696
Turkey	0.7705577	0.2714993	0.8615952	0.6332368	0.5913441
Brazil	0.9219275	0.9263884	0.9089294	0.886725	0.71754
Chile	0.5495008	0.8797673	0.9483746	0.4982688	0.835991
China	0.8208239	0.9444884	0.8024275	0.7425657	0.3699317
Colombia	0.5700642	0.7711676	0.6886	0.6559733	0.6154899
Czech	0.8779446	0.8819612	0.7049416	0.6690347	0.6136675

Estimated yearly values of the fraction of total variance in national market returns explained by the first principal component, from 1995 to 2014

Developed markets (DM) include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States

Emerging markets (EM) include: Egypt, Greece, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey, Brazil, Chile, China, Colombia, Czech Republic. World Markets include all markets classified as emerging and developed

Table 4: Estimated correlations of national market returns with the first component for the countries in the Developed Market Cluster, correlations are derived by multiplying individual country loadings in the first component by the first component's eigenvalue

Date	1995	1996	1997	1998	1999	2000	2001	2002
Australia	0.540576	0.7965	0.8001	0.739638	0.735745	0.609605	0.898679	0.875788
Austria	0.782934	0.501677	0.667926	0.848155	0.609999	0.718328	0.482831	0.535799
Belgium	0.856497	0.465702	0.823491	0.81133	0.561841	0.735925	0.598455	0.923449
Canada	0.570794	0.747878	0.803813	0.92063	0.870854	0.695075	0.860802	0.92901
Denmark	0.768283	0.146428	0.881038	0.745515	0.664511	0.703245	0.796611	0.884923
Finland	0.332404	0.453055	0.846138	0.857949	0.775876	0.32397	0.490406	0.608881
France	0.613833	0.565757	0.849851	0.919455	0.851123	0.881727	0.93855	0.976672
Germany	0.782324	0.284143	0.831659	0.883022	0.909982	0.686905	0.974034	0.969125
Hong Kong	0.548207	0.743663	0.865816	0.384314	0.685246	0.804113	0.862796	0.66965
Ireland	0.639473	0.718087	0.610007	0.85599	0.63876	0.412269	0.835285	0.871021
Israel	0.032355	0.752375	0.702826	0.556688	0.529067	0.515964	0.957687	0.335619
Italy	0.208172	0.662158	0.651218	0.783515	0.608661	0.561842	0.91702	0.956018
Japan	0.587277	0.220344	0.544291	0.675782	0.599297	0.482656	0.621978	0.470264
Netherlands	0.89862	0.707407	0.904429	0.897908	0.746446	0.884241	0.972439	0.984616
New Zealand	0.448089	−0.30972	0.815694	0.836794	0.748118	0.497739	0.816147	0.546126
Norway	0.587277	0.708812	0.597755	0.880279	0.611002	0.84402	0.927386	0.951649
Portugal	0.77683	−0.08994	0.865073	0.819165	0.318711	0.579124	0.531473	0.955621
Singapore	0.6877	0.756029	0.707281	0.612317	0.672537	0.348794	0.838874	0.478605
Spain	0.677933	0.587117	0.684633	0.980177	0.469539	0.831451	0.867182	0.93894
Sweden	0.547596	0.530906	0.856163	0.891248	0.886238	0.447777	0.961276	0.896441
Swiss	0.58392	−0.16891	0.84651	0.905744	0.990245	0.690362	0.831298	0.880157
UK	0.753632	0.643327	0.792675	0.865001	0.805306	0.736239	0.917418	0.959196
USA	0.678848	0.860299	0.703568	0.857949	0.764171	0.608348	0.893097	0.898824

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Table 4: (*Continued*)

Date	2003	2004	2005	2006	2007	2008	2009
Australia	0.755914	0.778771	0.77004	0.859543	0.916349	0.973233	0.873602
Austria	0.720772	0.743372	0.808311	0.916954	0.811656	0.97368	0.890117
Belgium	0.93931	0.849949	0.813981	0.899853	0.915968	0.957587	0.929075
Canada	0.648659	0.686658	0.815044	0.789509	0.84097	0.891423	0.887576
Denmark	0.73212	0.843098	0.786695	0.869315	0.867239	0.943728	0.864286
Finland	0.755548	0.779913	0.760826	0.821716	0.778916	0.871305	0.920183
France	0.978113	0.940539	0.879893	0.891709	0.909116	0.982622	0.965917
Germany	0.924302	0.912373	0.860049	0.983323	0.890842	0.95714	0.960835
Hong Kong	0.130317	0.611674	0.656642	0.90596	0.659375	0.93881	0.712263
Ireland	0.75445	0.204	0.658414	0.786251	0.598463	0.770719	0.789333
Israel	0.524198	0.701122	0.294479	0.721918	0.844777	0.874882	0.30701
Italy	0.725897	0.872406	0.830282	0.886009	0.816605	0.989327	0.978197
Japan	0.218172	0.240939	0.636443	0.956043	0.244411	0.9352	0.904938
Netherlands	0.944801	0.909708	0.785632	0.830633	0.896553	0.976363	0.959565
New Zealand	0.504065	0.638699	0.59888	0.74187	0.67803	0.917352	0.852005
Norway	0.908561	0.786384	0.790239	0.791952	0.836782	0.939705	0.808389
Portugal	0.673185	0.841956	0.54856	0.666542	0.518896	0.900364	0.914678
Singapore	0.414014	0.552676	0.506391	0.876237	0.892365	0.959375	0.901974
Spain	0.848527	0.889154	0.816107	0.778922	0.644528	0.922269	0.943473
Sweden	0.884035	0.906663	0.877767	0.84692	0.841732	0.964292	0.840995
Swiss	0.904168	0.878116	0.720428	0.889266	0.740465	0.897682	0.946861
UK	0.93748	0.853375	0.819651	0.850585	0.923582	0.94954	0.963376
USA	0.9254	0.911992	0.664084	0.8685	0.826123	0.926293	0.949402

Date	2010	2011	2012	2013	2014
Australia	0.98081	0.936923	0.857527	0.719378	0.475506
Austria	0.968146	0.914225	0.960261	0.7928	0.760167
Belgium	0.90963	0.904977	0.875357	0.803345	0.942093
Canada	0.839322	0.891106	0.924601	0.856458	0.743401
Denmark	0.921857	0.839826	0.877055	0.833416	0.720928
Finland	0.914433	0.818389	0.936063	0.864269	0.87396
France	0.983867	0.966766	0.944978	0.948236	0.953865
Germany	0.962906	0.915486	0.975119	0.888483	0.912129
Hong Kong	0.772945	0.876815	0.877904	0.970497	0.45874
Ireland	0.862467	0.838985	0.729323	0.595967	0.668847
Israel	0.74456	0.83226	0.59093	0.315558	0.342806
Italy	0.956356	0.921791	0.894036	0.838884	0.699525
Japan	0.824475	0.346775	0.896159	0.451076	0.216528
Netherlands	0.964653	0.9592	0.932243	0.849429	0.840785
New Zealand	0.925351	0.638486	0.814651	0.765853	0.480143
Norway	0.97688	0.938184	0.931818	0.914259	0.609988
Portugal	0.884302	0.896991	0.84649	0.758042	0.809394
Singapore	0.896529	0.851175	0.832056	0.82873	0.544709
Spain	0.912687	0.838565	0.791303	0.927928	0.85006
Sweden	0.941071	0.979376	0.948374	0.866613	0.943877
Swiss	0.847619	0.906238	0.958138	0.895903	0.943877
UK	0.985177	0.956678	0.964082	0.95097	0.864329
USA	0.911813	0.960882	0.9038	0.754136	0.794055

Table 5: Estimated correlations of national market returns with the first component for the countries in the Emerging Market Cluster, correlations are derived by multiplying individual country loadings in the first component by the first component's eigenvalue

Date	1995	1996	1997	1998	1999	2000	2001	2002
Egypt	−0.2985	−0.45923	0.543747	0.1742	0.060288	0.272064	0.659066	−0.24705
Greece	0.842549	0.336465	0.751297	0.1992	−0.61394	0.090048	0.532132	0.398122
Hungary	0.767854	0.910102	0.713906	0.257	0.101936	0.672836	0.73367	0.806537
India	0.603135	−0.21747	0.713272	0.1591	−0.316	0.657948	0.895608	0.397213

(*Contd...*)

Table 5: (*Continued*)

Date	1995	1996	1997	1998	1999	2000	2001	2002
Indonesia	0.759771	0.769256	0.623598	0.1843	0.691123	0.407255	0.370901	0.425672
Korea	0.445941	0.017808	0.635956	0.1002	0.622972	0.620488	0.974809	0.727518
Malaysia	0.819695	0.470835	0.82481	0.2075	0.495407	0.213713	0.1193	0.583104
Mexico	0.36595	0.799746	0.709153	0.2464	0.867326	0.540286	0.919298	0.912198
Peru	0.602856	0.391778	0.713589	0.2231	0.512299	0.638738	0.297711	0.805628
Philippines	0.894111	0.806491	0.547867	0.2239	0.883053	0.432469	0.688059	0.198001
Poland	0.409987	0.8529	0.52125	0.2328	0.534142	0.726384	0.644216	0.825307
Russia	0.512274	0.393127	0.880896	0.2408	0.757235	0.39717	0.927076	0.745986
South Africa	0.556868	0.880961	0.815938	0.2225	0.802378	0.802985	0.792717	0.655765
Taiwan	0.571083	0.063408	0.635956	0.2166	0.723742	0.47281	0.783878	0.894033
Thailand	0.874044	0.77843	0.662256	0.1797	0.873733	0.376759	0.781757	0.635783
Turkey	0.425873	0.56905	0.457559	0.1836	0.393762	−0.0365	0.82065	0.58704
Brazil	0.213773	0.751718	0.876777	0.2522	0.65763	0.841645	0.894901	0.729032
Chile	0.619858	−0.16729	0.947755	0.2589	0.772089	0.549651	0.894901	0.741142
China	0.709603	0.570669	0.397037	0.1967	0.632874	0.116462	0.665076	0.501361
Colombia	−0.03846	−0.19751	0.59508	0.1491	0.392597	−0.23941	0.715638	0.452315
Czech	0.487748	0.135719	0.216422	0.2458	0	0.535723	0.848229	0.285497
USA	0.289861	0.505372	0.633738	0.2535	0.746459	0.499464	0.829489	0.856188

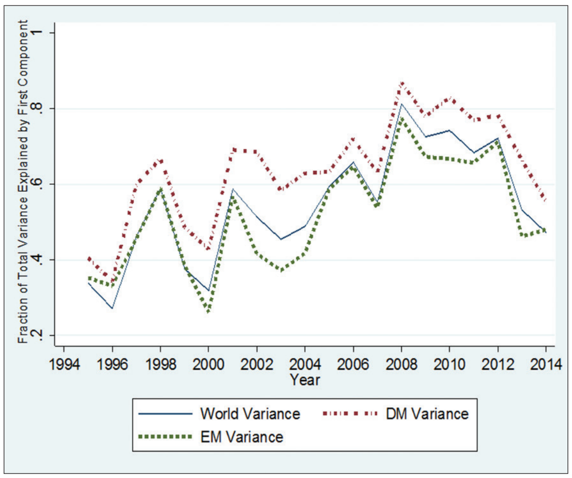
Date	2003	2004	2005	2006	2007	2008	2009
Egypt	0.560636	0.1152	0.147001	0.776218	0.520607	0.929681	0.759798
Greece	0.787866	0.460798	0.863674	0.905965	0.729675	0.952386	0.818658
Hungary	0.556629	0.786995	0.796463	0.853538	0.624109	0.951147	0.927146
India	0.492237	0.561143	0.814434	0.766034	0.858967	0.865693	0.867131
Indonesia	0.565214	0.334685	0.377745	0.876923	0.862406	0.902021	0.925607
Korea	0.813623	0.764562	0.880207	0.849389	0.780223	0.880967	0.838278
Malaysia	0.429277	0.775172	0.536247	0.694749	0.708355	0.875188	0.745948
Mexico	0.639909	0.873395	0.906085	0.925955	0.5574	0.906562	0.9283
Peru	0.41325	0.416234	0.868706	0.793191	0.823549	0.840511	0.719019
Philippines	0.301352	−0.1634	0.349351	0.303246	0.743429	0.707994	0.757489
Poland	0.788725	0.8355	0.922977	0.761508	0.848995	0.901196	0.826352
Russia	0.382915	0.509607	0.861517	0.822987	0.439112	0.820695	0.829814
South Africa	0.609859	0.823677	0.907522	0.871265	0.774033	0.9536	0.903678
Taiwan	0.309938	0.724848	0.725299	0.647603	0.713513	0.820695	0.81558
Thailand	0.499106	0.559021	0.785321	0.761131	0.644397	0.898306	0.757489
Turkey	0.689991	0.652697	0.852891	0.847881	0.866876	0.788907	0.817119
Brazil	0.654218	0.772747	0.822341	0.887861	0.940806	0.899132	0.790959
Chile	0.711169	0.619956	0.716314	0.820724	0.703198	0.892114	0.325847
China	0.621879	0.685135	0.936994	0.850144	0.753745	0.813677	0.847126
Colombia	0.713172	0.434121	0.667793	0.76	0.619295	0.922663	0.837893
Czech	0.511412	0.870363	0.793228	0.840714	0.775065	0.901196	0.88829
USA	0.901768	0.68756	0.721346	0.855047	0.61345	0.897893	0.91522

Date	2010	2011	2012	2013	2014
Egypt	0.573242	0.429829	0.678333	0.658657	−0.0361
Greece	0.852778	0.562844	0.720283	0.84475	0.1931
Hungary	0.935107	0.828115	0.916184	0.439742	0.1091
India	0.85431	0.716762	0.858404	0.833279	0.2518
Indonesia	0.830185	0.833815	0.788354	0.464597	0.0983
Korea	0.917493	0.905263	0.946262	2.010703	0.2538
Malaysia	0.848566	0.936807	0.820411	0.417436	0.2855
Mexico	0.832866	0.943648	0.861965	0.661843	0.2247
Peru	0.55869	0.549163	0.784001	0.514625	0.1999
Philippines	0.749388	0.820514	0.822785	0.745012	0.1687
Poland	0.959998	0.940227	0.909061	0.590783	0.2
Russia	0.848949	0.857378	0.982276	0.823719	0.2107
South Africa	0.934725	0.780609	0.906686	0.680644	0.2729
Taiwan	0.886476	0.773768	0.653796	0.758076	0.2608
Thailand	0.695012	0.87866	0.917372	0.801413	0.2085
Turkey	0.806061	0.278952	0.849301	0.728442	0.2203
Brazil	0.919407	0.947068	0.945471	0.937478	0.2673

(*Contd...*)

Date	2010	2011	2012	2013	2014
Chile	0.560222	0.925786	0.951011	0.592058	0.2458
China	0.82559	0.96227	0.846926	0.591421	0.1523
Colombia	0.582815	0.822794	0.764213	0.594289	0.2449
Czech	0.872307	0.836856	0.649838	0.755209	0.135
USA	0.899112	0.866119	0.869881	0.677457	0.2438

Figure 1: Estimated yearly values of the fraction of total variance in national market returns explained by the first principal component from 1995 to 2014. Developed markets (DM) include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Emerging markets (EM) include: Egypt, Greece, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey, Brazil, Chile, China, Colombia, Czech Republic. World Markets include all markets classified as emerging and developed



The lines in Figure 1 describe the dynamics of the fraction of variance explained by the first component for all three clusters of countries. Figure 1 variance explained by the first component, 1995-2015.

The three lines follow uneven paths and to large extent move in a lockstep. The line representing the developed markets cluster is always above the line for the emerging markets cluster, illustrating that developed markets cluster is always more homogeneous than the emerging markets cluster. The difference seems to be the greatest between 2001 and 2005 and then again between 2008 and 2012. The smallest difference is in 1996 when the two lines overlap. The difference is also small around 1999, 2001, and in 2008.

The line representing the fraction of variation explained by the first component for the world markets cluster is located slightly above the line representing emerging markets, but below the line representing developed markets. This implies, that the influence of the common component for the cluster of world markets is stronger than for the emerging markets cluster, but still weaker than for the developed markets cluster.

The fraction of total data variation explained by the first component for all three clusters of markets in 2014 is slightly higher than in 1995. This suggests that over the past 20 years the fraction of common variation increased for all three sets of markets.

In summary, my analysis in this subsection suggests that the fraction of total data variation explained by the first component peaks at the same time for all three clusters. This is a strong indication that the vulnerability of markets to common factors increased simultaneously, regardless of the type of market. The US returns, are always highly correlated with the common component, regardless of the market cluster and whether the explained variance peaks or troughs.

The next subsection investigates the dynamics in the number of significant components.

3.2. Significant Components

In this subsection I analyze the variability in the number of significant components.

According to Kaiser (1960), significant components are those with eigenvalues <1. Each component represents a common factor causing variability. The greater the number of common factors, the more heterogeneous the markets, and therefore the greater the opportunities for portfolio diversification.

First I begin by discussing the number of significant components for the world markets cluster and then proceed with the developed and emerging markets clusters.

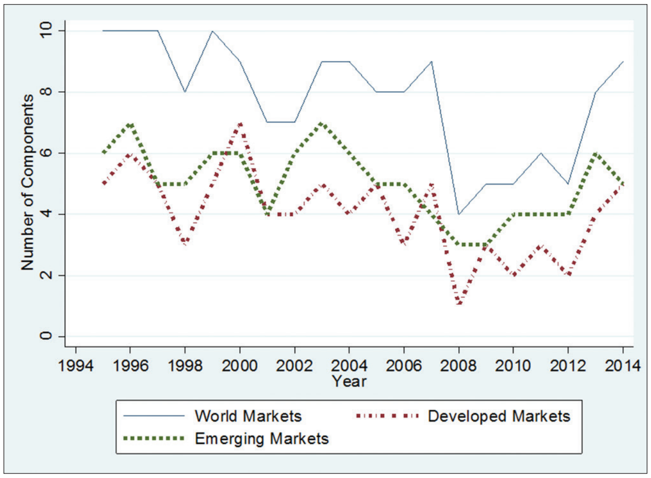
The number of significant components derived for the world markets cluster is described in the fourth column of Table 2.

The largest number of significant components is 10 and is recorded in 1995, 1996 and 1999. This means that in these years there was the greatest number of uncorrelated factors moving the markets. Therefore, the markets under study were most heterogeneous and thus offered the highest (according to this criterion) diversification opportunities.

The smallest number of significant components is 4 and is recorded in 2008. This means in 2008 there were the smallest number of unrelated factors moving the markets. Therefore, the markets under study were the least heterogeneous and thus offered the lowest diversification opportunities.

Next, I proceed with analyzing the developed markets cluster. The number of significant components derived when only developed

Figure 2: Number of components with variance greater than 1. Estimated number of principal components with Eigen values greater than 1 for every year from 1995 to 2014. Developed markets (DM) include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Emerging markets (EM) include: Egypt, Greece, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey, Brazil, Chile, China, Colombia, Czech Republic. World Markets include all markets classified as emerging and developed



markets are considered along with the US is described in the seventh column of Table 2.

The largest number of significant components is 7 and is recorded in 2000. This means in this year there was the greatest number of independent factors moving the markets. Therefore, the developed markets under study were most heterogeneous and thus offered the highest (according to this criterion) diversification opportunities.

The smallest number of significant components is 1 and is recorded in 2008. This means in 2008 there were the smallest number of independent factors moving the markets. Therefore, the markets under study were the least heterogeneous and thus offered the lowest diversification opportunities.

Finally, I describe the emerging markets cluster.

The number of significant components derived when only emerging markets are considered along with the US is described in the 10th column of Table 2.

The largest number of significant components is 7 and is recorded in 1996 and 2003. This means in these years there were the greatest number of factors moving the markets. Therefore, the emerging markets under study were most heterogeneous and thus offered the highest (according to this criterion) diversification opportunities.

The smallest number of significant components is 3 and is recorded in 2008 and 2009. This means in 2008 and 2009 there were the smallest number of independent factors moving the markets. Therefore, the emerging markets under study were the least heterogeneous and thus offered the lowest diversification opportunities.

Figure 2 describes the dynamics of the number of significant components for all three clusters.

The line representing the world markets cluster peaks in 1995, 1996, and 1999 and troughs in 2008. The line representing developed markets cluster peaks in 2000 and troughs in 2008. Finally, the line representing emerging markets cluster peaks in 1996 and 2003 and troughs in 2008 and 2009. The three graphs peak at mostly different years, however, they all trough almost simultaneously in 2008. This tells us, that while market heterogeneity may be increasing at different times, it may be decreasing simultaneously.

The line representing the developed market cluster seems to be more uneven than the line representing the emerging markets cluster. This implies more frequent and abrupt changes in the number of factors driving the volatility and thus more frequent and abrupt changes in heterogeneity levels.

It should be pointed out that the line representing the world markets cluster is always above the lines representing emerging and developed markets. This tells us that when considered together, developed and emerging markets are more heterogeneous than when considered separately. Therefore portfolio diversification may be more beneficial when investors consider a combination of emerging and developed markets rather than when market clusters are considered separately.

Finally, the number of significant components in 2014 is lower than in 1996 for all three clusters. This tells us that the heterogeneity of all market clusters decreased during the period of study.

Overall, my analysis in this subsection further indicates that heterogeneity of markets decreases simultaneously, regardless of which market cluster is considered.

In the next subsection, I discuss my portfolio diversification indices and quantify the diversification opportunities offered by the different market clusters.

3.3. Index of Portfolio Diversification

In this subsection, I describe my indices of portfolio diversification and quantify the diversification opportunities offered to US investors by the international financial markets.

I construct three separate indices of portfolio diversification: One for the world markets cluster, a second one for the developed markets cluster, and a third one for the emerging markets cluster.

First I begin by describing the world markets cluster.

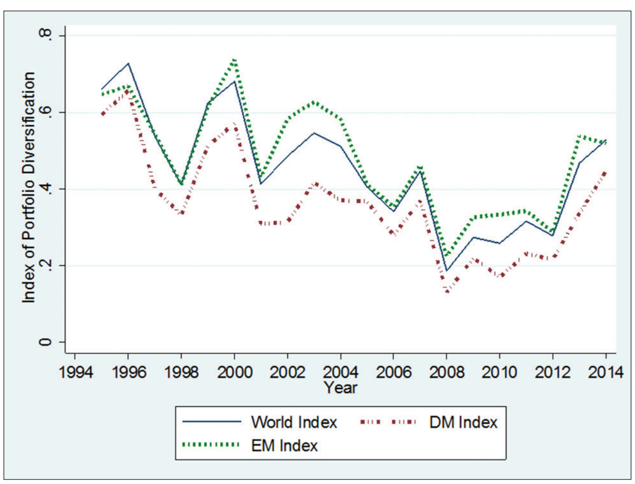
The index of portfolio diversification constructed for the world market cluster (World Market Index) is described in the third column of Table 2. The largest value of the index is recorded in 1996 and equals 0.72. This means, that in 1996 the level of diversification opportunities offered to US investors by the international financial markets was greatest relative to other periods.

The smallest index value is recorded in 2008 and equals 0.18. This means, that in 2008, the level of diversification opportunities offered to US investors by the international financial markets was smallest relative to other years.

Next, I proceed with analyzing the index of portfolio diversification for the developed markets cluster.

The index of portfolio diversification constructed for the developed markets cluster (Developed Market Index) is described in the sixth column of Table 2. The largest index value is recorded in 1996 and equals 0.65. This means, that in 1996 the level of diversification opportunities offered to US investors by developed markets was greatest relative to other years. The smallest index value is recorded in 2008 and equals 0.13. This means, that in 2008, the level of diversification opportunities offered to US investors by developed markets was smallest relative to other years.

Figure 3: Index of Portfolio diversification. Estimated yearly values of the index of portfolio diversification from 1995 to 2014. Developed markets (DM) include: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States. Emerging markets (EM) include: Egypt, Greece, Hungary, India, Indonesia, South Korea, Malaysia, Mexico, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, Turkey, Brazil, Chile, China, Colombia, Czech Republic. World Markets include all markets classified as emerging and developed



Finally, I analyze the portfolio diversification index for the emerging markets cluster.

The index of portfolio diversification constructed for the emerging markets cluster (emerging market index) is described in the 9th column of Table 2. The largest index value is recorded in 2000 and equals 0.73. This means, that in 2000 the level of diversification opportunities offered to US investors by emerging markets was greatest relative to other years. The smallest index value is recorded in 2008 and equals 0.2253. This means, that in 2008, the level of diversification opportunities offered to US investors by emerging markets was smallest relative to other years.

Figure 3 describes the dynamics of the three portfolio diversification indices. All three indices follow uneven paths and to large extent move together.

The line representing the world markets index peaks in 1996 and troughs in 2008; the line representing developed markets index peaks in 1996 and troughs in 2008; and the line representing emerging markets index peaks in 2000 and troughs in 2008. The three indices peak at mostly different years, however, they all trough almost simultaneously in 2008. This tells us again, that diversification opportunities offered by different clusters may be increasing at different times, but decreasing at the same time.

The line representing the emerging market index is always above the line representing developed markets. This suggests that the diversification opportunities offered to US investors by emerging markets are always superior to the diversification opportunities offered by developed markets. The line representing the emerging market index is also more uneven relative to the line representing the developed market index. This suggests greater dynamics in the level of diversification opportunities offered by emerging markets. The difference between the two indices is greatest around 1999 and then between 2001 and 2004 and between 2009 and 2012. During these periods diversification with emerging markets is most dominant. The difference between the two lines is smallest in 1996, 1999 and between 2005 and 2009. During these periods diversification with emerging markets is not as dominant.

The line representing the world markets index is located slightly above the line representing the developed markets index, but below the line representing emerging markets. This indicates that the level of diversification opportunities offered by a mixture of emerging and developed markets is dominated by the level of diversification opportunities offered by emerging markets alone.

Finally, the levels of all three indices are lower in 2014 relative to 1996, implying that the diversification opportunities available

Table 6: Estimates from deterministic log-linear trend models

Statistic	World markets	Developed markets	Emerging markets
Coefficient (β_1)	−3.8	−4.3	−3.12
Standard error	1.13	1.31	1.05
P value	0.04	0.04	0.08
95%	−6.19627-1.40867	−7.10318-1.58402	−5.33186-0.91617

to US investors decreased altogether, regardless of the types of markets considered.

The analysis in this subsection indicates a highly dynamic evolution of the portfolio diversification opportunities offered to US investors. Over the period of study, the potential diversification opportunities abroad decreased altogether. Furthermore, the analysis indicates that while diversification opportunities offered by different clusters increase at different times, they may be decreasing simultaneously, regardless of the type of market considered.

One implication of this analysis is that while international diversification may provide some protection against country specific shocks, it most likely bears no significance when global shocks are considered.

In summary, my analysis in this section suggests that the homogeneity of international markets as well as their vulnerability to common factors increases simultaneously, regardless of the type of market. This leads to a simultaneous decrease in portfolio diversification opportunities offered to US investors abroad. Consequently, international diversification is unlikely to provide protection against global shocks.

In the following subsection, I am going to present my trend analysis of the evolution of the three indices of portfolio diversification.

4. TREND MODELS

In this section I describe the results from the trend analysis of my indices of portfolio diversification. Subsection 4.1 describes the results from the estimation of log-linear deterministic models. Subsection 4.2 describes the results from the estimation of quadratic models and finally, in subsection 4.3 I describe my trend model forecast of the future evolution of the three indices.

4.1. Log-linear Deterministic Trend Models

In this subsection, I describe the results from the log-linear regressions of my indices on a deterministic yearly time variable. The obtained estimate of the coefficient multiplying the time variable (the independent variable), when multiplied by 100 represents the average percentage rate of change of the index (the dependent variable) per year.

I estimate three separate trend models, one for each index. The result from the three regressions are summarized in Table 6. All values are measured in percent.

The table provides estimates from the regression of the logarithm of the index of portfolio diversification on a time variable. The same deterministic log-linear trend model is estimated separately for the index of portfolio diversification for the three clusters of markets: World, developed, and emerging. All values are multiples of 100 and are thus measured in percent. Let Y_t be the logarithm of the index of portfolio diversification for a cluster. The estimated model for each cluster is specified as follows:

$$Y_t=\beta_0+\beta_1 t+\varepsilon_t,\ \varepsilon_t \rightarrow WN(0,\ \sigma_\varepsilon^2),\ \text{for } t = 1,2,3 \ldots 20.$$

Where Y_t stands for an index of portfolio diversification and t stands for time. The model for each cluster is based on twenty observation of the respective index of portfolio diversification for the period from 1995 to 2014.

The second row of Table 6 contains the estimates of the coefficient multiplying the time variable in each regression.

The second column of the second row offers the respective value for the coefficient when the dependent variable is the world market index. Per my estimation, this value is −3.8%, implying, that the values of world market index decrease on average by 3.8% per year. In other words, the portfolio diversification benefits offered to US investors by the international markets as a whole decrease on average by 3.8% per year.

The 3rd column of the second row offers the respective value for the coefficient when the dependent variable is the developed market index. Per my estimation, this value is −4.3%, implying, that the values of the developed market index of diversification decrease on average by 4.3% per year. In other words, the portfolio diversification benefits offered to US investors by developed markets decrease on average by 4.3% per year.

The fourth column of the second row offers the respective value for the coefficient when the dependent variable is the emerging market index. Per my estimation, this value is −3.12%, implying, that the values of the emerging market index of diversification decreases on average by 3.12% per year. In other words, the portfolio diversification benefits offered to US investors by emerging markets decrease on average by 3.12% per year.

My analysis so far indicates that the diversification opportunities offered by developed markets cluster were the fastest to decrease, followed by the world markets cluster. The diversification opportunities offered by emerging markets cluster were the slowest to decrease.

The third row of Table 6 offers the standard errors for the three estimates discussed above.

The largest standard errors are recorded for the coefficient multiplying the time variable in the regression when the dependent variable is the developed market index. This value is 1.31% and is recorded in the third column of the third row. The second largest standard errors are recorded for the coefficient multiplying the time variable in the regression when the dependent variable is the world market index. Its value is 1.13% and is recorded in the second column of the third row. The smallest standard errors are recorded for the coefficient multiplying the time variable in the regression when the dependent variable is the emerging market index. Its value is 1.05% and is recorded in the fourth column of the third row.

The analysis of the third row of Table 6 indicates, that the developed market index is the most variable, followed by the world market index and the emerging market index.

Figure 4: Predicted trends by log-linear deterministic trend model. (a) Panel 1: World market cluster, (b) Panel 2: Developed market cluster, (c) Panel 3: Emerging market cluster

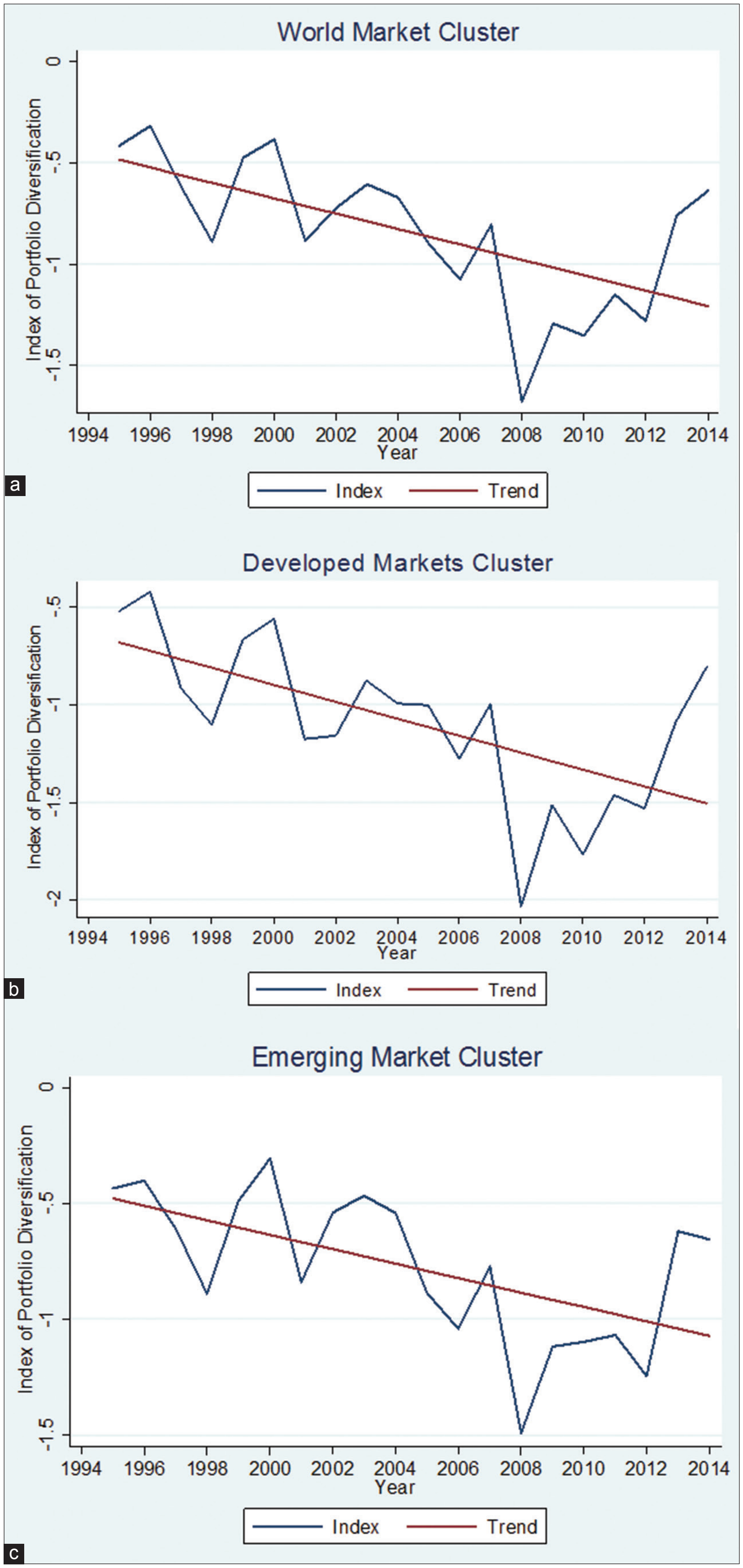
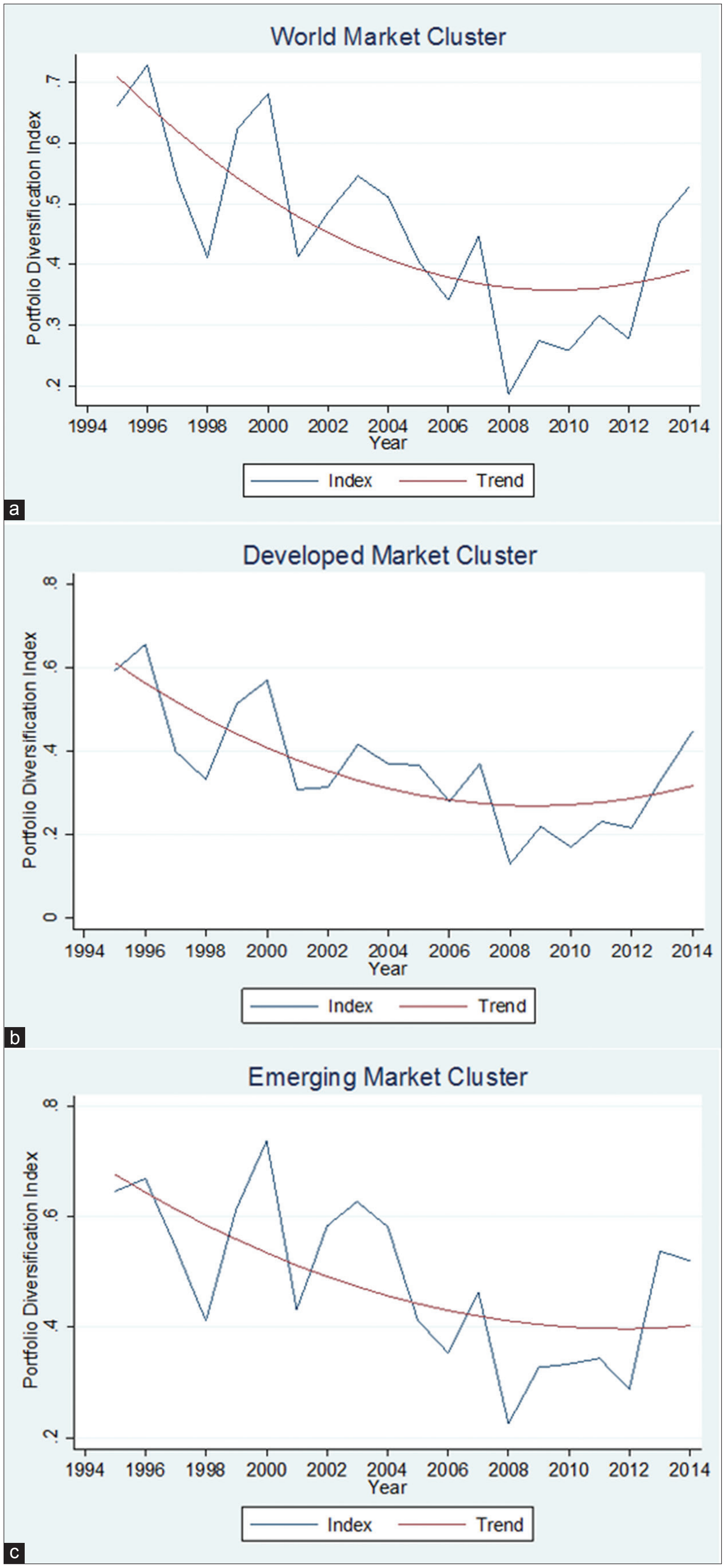


Figure 5: Predicted trends by quadratic deterministic trend model, (a) Panel 1: World market cluster, (b) Panel 2: Developed market cluster, (c) Panel 3: Emerging market cluster



Overall, my analysis in this section indicates that the portfolio diversification opportunities offered to US investors by each cluster follow a declining path. The fastest decline is observed for developed markets and the slowest for the emerging markets. Figure 4 offers a visual summary of the three models.

Each panel graphs together the logarithmic portfolio diversification index along with the predicted trend for each cluster of markets. The deterministic log-linear trend model for each cluster is specified as follows:

$Y_t = \beta_0+\beta_1 t+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2)$ for t = 1,2,3 … 20

The regression for each cluster is based on 20 observation of the respective index of portfolio diversification for the period from 1995 to 2014.

In the next subsection, I perform further analysis on the indices of diversification by exploring quadratic trend models.

4.2. Quadratic Deterministic Trend Models

In this subsection, I describe the results from the estimation of quadratic trend models.

An inspection of Figures 3 and 4 as well as a specification analysis based on Schwarz-Bayesian Criterion suggest that quadratic models outperform simple linear and log-linear trend models. Therefore, to further explore the indices of portfolio diversification, I proceed with the analysis of quadratic deterministic models. Furthermore, I choose to work with levels, rather than logarithms to add meaning to the predicted index values.

The three panels of Figure 5 visually summarize the outcome of the estimation of the quadratic trend model for all three markets. Panel 1 describes the model outcome when estimated for the world market cluster; Panel 2 describes the model outcome for the developed markets cluster, and finally Panel 3 describes the model outcome for emerging markets cluster.

Each panel graphs together the portfolio diversification index along with the predicted trend for each cluster of markets. The quadratic deterministic trend model for each cluster is specified as follows: $Y_t = \beta_0+\beta_1 t+\beta_1 t^2+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2)$ for t = 1,2,3 … 20.

The regression for each cluster is based on twenty observation of the respective index of portfolio diversification for the period from 1995 to 2014.

The predicted values for all three indices seem to be decreasing steadily until around 2008. This implies the diversification opportunities offered to US investors by foreign markets on average have been decreasing, despite some temporary ups and downs. The fastest decrease, on average seems to be for the world market cluster, while the slowest for the emerging market cluster. The steady decrease seems to level off for all three clusters between 2008 and 2012. Beginning in 2012, the observed indices sharply increase, implying the diversification opportunities begin to increase. The predicted values for the world and developed markets indices reflect this by also beginning to increase, while the predicted values for the emerging market index remained largely unaffected. One possible explanation for this could be that after 2012, the heterogeneity between the US and developed markets began to increase faster than the heterogeneity between the US and emerging markets, thus causing the diversification opportunities offered by developed markets to increase at a faster rate.

In summary, my analysis in this subsection indicates that predicted trends initially decrease, but after 2012 either level of or begin to increase.

In the next subsection, I build on the quadratic model to construct a forecast of the expected evolution of the three portfolio diversification indices.

4.3. Trend Model Forecasts

In this subsection, I describe the 5-year index point and interval forecast estimates obtained from the recursive estimation of quadratic trend models.

For each cluster, the forecast values are obtained by estimating separate models. The results from the three regressions are summarized in the three panels of Table 7.

The Table 7 provides estimates of the 5-year trend point and interval forecast values obtained from the recursive estimation of a quadratic trend model. For each cluster, the model is specified as follows:

$Y_t = \beta_0+\beta_1 t+\beta_2 t^2+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2)$ for t = 1,2,3 …. 20

Where, Y_t is the portfolio diversification index for each cluster and t is a deterministic time variable.

For each year, the optimal forecast is: $E(Y_{t+h}/I_{t=h-1}) = \beta_0+\beta_1(t+h)$, For h = 1….5 and I_t is the information set up until period t. The

Table 7: Trend point and interval forecasts

Year	Trend forecast	Standard error	Confidence interval
2015	0.4074104	0.1351084	0.142598-0.6722227
2016	0.4272001	0.1457208	0.1415872-0.7128129
2017	0.4503106	0.1588228	0.1390178-0.7616034
2018	0.4767419	0.174406	0.1349062-0.8185776
2019	0.506494	0.1924101	0.1293703-0.8836178

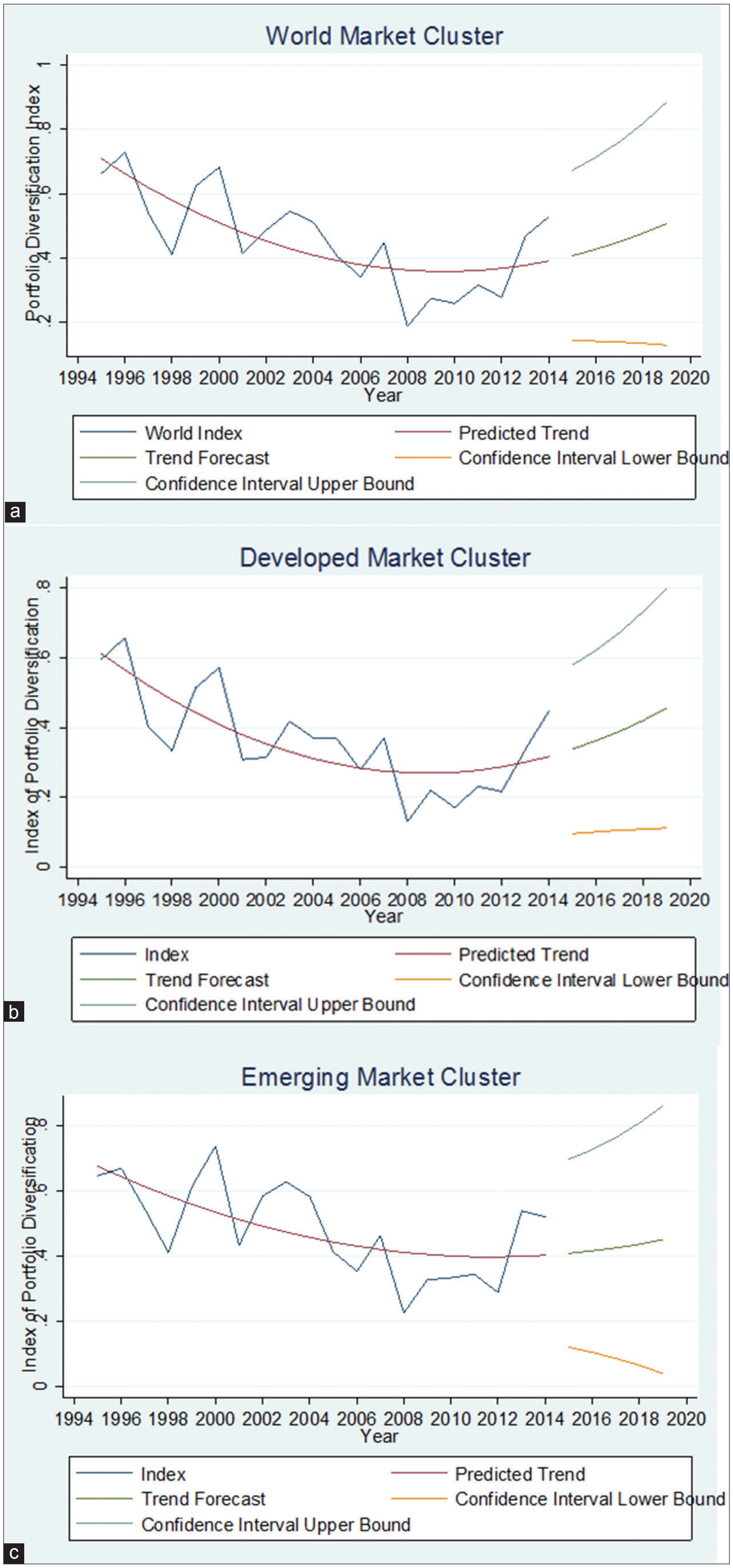
Panel 2: Developed markets

Year	Trend forecast	Standard error	Confidence interval
2015	0.3376121	0.122707	0.0971063-0.5781178
2016	0.3615106	0.1323454	0.1021136-0.6209076
2017	0.3889915	0.1442448	0.1062716-0.6717113
2018	0.4200547	0.1583976	0.1095954-0.730514
2019	0.4547003	0.1747491	0.112192-0.7972085

Panel 3: Emerging markets

Year	Trend forecast	Standard error	Confidence interval
2015	0.4079724	0.1472385	0.1193849-0.6965599
2016	0.4155025	0.1588038	0.104247-0.726758
2017	0.4250286	0.1730821	0.0857876-0.7642696
2018	0.4365506	0.1900643	0.0640244-0.8090767
2019	0.4500685	0.2096848	0.0390862-0.8610508

Figure 6: Trend forecast each panel graphs together the portfolio diversification index along with predicted trend. Each panel also offers the trend forecast and confidence intervals (a) Panel 1: World market cluster, (b) Panel 2: Developed market cluster, (c) Panel 2: Emerging market cluster



respective interval forecast at the 95% confidence interval is: $E(Y_{t+h}/I_t) - 1.96\sigma_{\varepsilon+h}$, $E(Y_{t+h}/I_{t+h-1}) - 1.96\sigma_{\varepsilon+h}$, where σ_ε is the standard deviation of the white noise term in the linear trend model.

The model for each cluster is based on twenty observation of the respective index of portfolio diversification for the period from 1995 to 2014.

Panel 1 of Table 7 describes the forecast estimates for the World market index. The second column offers the index point forecast estimates provided by the quadratic trend model. My estimation indicates that the index of portfolio diversification is expected to steadily increase to 0.506 in 2019. This implies, that there may be an increase in diversification opportunities offered to US investors by international markets.

The 4th column of Panel 1 offers the 95% confidence intervals. While the point forecast is steadily increasing, the confidence intervals suggest that index decreases in any given year are not unlikely. The results indicate that in 2019 the diversification index may increase to as high as 0.883 but also decrease to as low as 0.129. In other words, the diversification opportunities available may spike up, but may also decrease significantly.

Panel 2 of Table 7 describes the forecast estimates for the Developed Market Index. The second column offers the point forecast estimates. My estimation indicates that the index of portfolio diversification is expected to steadily increase to 0.454 in 2019. The fourth column of Panel 2 offers the 95% confidence intervals. The results indicate that in 2019 the diversification index may increase to as high as 0.797 but also decrease to as low as 0.112.

Finally, Panel 3 of Table 7 describes the forecast estimates for the emerging market index. The second column offers the point forecast estimates. My estimation indicates that the index of portfolio diversification is expected to steadily increase to 0.45 in 2019. The fourth column of Panel 3 offers the 95% confidence intervals. The results indicate that in 2019 the diversification index may increase to as high as 0.883 but also decrease to as low as 0.039.

In summary, my analysis in this subsection indicates that the level of diversification opportunities offered to US investors abroad are expected to increase, however, a decrease is not unlikely. The results from this analysis are also visually summarized in the three panels of Figure 6.

5. CONCLUSION

In this study, I utilize PCA to create an index of portfolio diversification- a quantifiable measure of diversification opportunities offered to US investor by financial markets abroad.

In my work, I explore three market clusters: Developed, emerging, and world (emerging and developed). I find that the homogeneity of international markets as well as their vulnerability to common factors increased simultaneously, regardless of the type of market. This lead to a simultaneous decreases in portfolio diversification opportunities offered to US investors abroad. Consequently, my study suggests that international portfolio diversification is unlikely to provide protection against global shocks.

During the period under study, the portfolio diversification indices for all three clusters display considerable dynamics. This is suggestive of highly variable benefits from investing abroad. In addition, I find that while the diversification opportunities offered by all three market clusters on average decrease between 1995 and 2014, after 2012 they either level off or begin to increase. Finally, my analysis indicates that the level of diversification opportunities are expected to increase, however, decreases are not unlikely.

A logical extension of the research presented in this article is exploring the factors affecting the levels of portfolio diversification, as well as their dynamics and evolution. Investigation of portfolio diversification benefits further by constructing investment opportunity sets may be also worthwhile. Finally, this analysis could be extended to a variety of markets and assets of interest.

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APPENDIX A

Principal Component Analysis (PCA)

PCA is a variable reduction statistical method that is often used to identify patterns in data and describe possible underlying data structures. It is especially useful in the analysis of datasets containing a relatively large number of variables, where those variables are believed to be imperfect measures of one or more underlying constructs. This implied redundancy in variables allows for the reduction the observed variables into a smaller number of principal components (artificial unobserved variables) that account for most of the variance in the observed variables.

In the process of data reduction, PCA extracts the eigenvectors from the Eigen decomposition of the correlation matrix of the original variables. The eigenvectors are then used to create a series of uncorrelated linear combinations of the variables (PCs) that explain the total variance in the dataset. The number of extracted principal components is equal to the number of original variables and the sum of the variances of all components is equal to the sum of the variances of the original variables. The use of a correlation matrix results in the observed variables being standardized with a variance equal to 1. Thus, the total variance in the dataset is equal to the number of the variables analyzed. In practice, only those components with relatively high variance are kept for further analysis.

PCA is founded on a set of simple assumptions and requires no probability distribution specified for the observed data. Shlens (2009) outlines those assumptions as follows:

1. Linearity: The relationship between the observed variables is linear.
2. PCs are orthogonal. This assumption makes PCA soluble with linear algebra decomposition techniques.
3. Large variances have important structure - PCs with larger associated variances represent interesting structure, while those with lower associated variances represent noise.

As an illustration of how principal components are derived, consider a set of variables X_j (e.g. national stock market indices), such that $j = 1 \ldots K$. Let $X_1, X_2, X_3 \ldots X_k$ are measured on even observational intervals (monthly returns) and are put together to form a linear combination such that

$$F_1 = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 + \alpha_4 X_4 + \ldots + \alpha_k X_k$$

Where, F_1 is referred to as the first principal component of the K observed variables X.

The coefficients of the component F_1, summarized by the vector $A_1' = (\alpha_1^1, \alpha_2^1, \alpha_2^1 \ldots \alpha_k^1$ are called variable loadings A_1'. is selected such that the sample variance of F_1 is maximized:

$$Var(F_1) = A_1' Z_{xx} A_1$$

Where Z_{xx} represents the sample correlation matrix.

The coefficients contained in A_1' are elements of an eigenvector of the sample correlation matrix Z_{xx} selected such that $A_1' A_1 = 1$. This allows for the variance of the component F_1 to be represented by the eigenvalue λ_1 corresponding to the eigenvector A_1.

In PCA, the number of components is equal to the number of originally observed variables. If there are K observed variables, then there are K principal components and the variance of each F_j, j = 1…. K; is represented by the eigenvalue λ_j corresponding to the eigenvector $A_1^{'}$.

Each successive component is derived such that it is orthogonal to the preceding one(s) and explains the maximum possible fraction of the total variance that remains unexplained by the previous components. For example, F_3 explains the maximum possible fraction of total variance, that remains unexplained after F_1 and F_2 have been derived.

Each component F_j, j = 1…K, can be determined from the sample correlation matrix Z_{xx} by solving the following characteristic equation:

$$|Z_{xx}-\lambda I|=0$$

This equation has K ordered roots, called eigenvalues such that:

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \geq \ldots . \geq \lambda_k \geq 0$$

A distinct property of the eigenvalues is that $\lambda_1 = Var(F_1)$, $\lambda_2 = Var(F_2)$, $\lambda_3+Var(F_3)$ etc. The total variance in the dataset is then equal to the sum of the eigenvalues such that:

$$\lambda_1+\lambda_2+\lambda_3+\ldots .+\lambda_k = K$$

The proportion of the total variance explained by the first principal component is given by λ_1/K, the proportion of the variance explained by the second component is given by $\lambda_{2/}K$ etc.

Principal components are ranked per the variance they explain. Keiser (1960) advises that only components with a variance greater than the variance of a single variable, those with eigenvalues greater than one, are considered for further analysis. Per this criterion, other components are considered less significant and constitute noise.

Finally, if the variable loadings in a component are multiplied by the square root of the respective component's eigenvalue, the product will produce estimates of the correlations between the variables and the principal component.

More in-depth analysis and detailed discussions of PCA are offered in Stevens (1996), Smith (2002), Marida et.al. (1979), and Jolliffe (2002) among many others.

APPENDIX B

Index of portfolio diversification

Here I describe my approach in applying the PCA for quantifying portfolio diversification opportunities.

The steps in the process are outlined as follows:

1. I perform PCA on country monthly returns for each year from 1995 to 2014. This provides for as many components as there are countries in the data set. Each component is based on an eigenvector with a respective eigenvalue.
2. Rank PCs per size of eigenvalues. Each eigenvalue measures the variance explained by a particular component and the sum of all eigenvalues measure the total variance in the data set.
3. Obtain the proportion of total variance explained by the first component. This is done by dividing the respective eigenvalue by the sum of all eigenvalues.
4. Subtract the proportion of total variance explained by the first component from one to obtain the measure of portfolio diversification.
5. Repeat this procedure separately for each year from 1995 to 2015. The measures of diversification for each year are stacked in a vector to form the index of portfolio diversification.
6. Repeat all steps above separately for each cluster of markets.

APPENDIX C

Log-linear deterministic trend models

I investigate the average rate of change of the three indices of portfolio diversification by constructing log-linear deterministic trend models for each index. The same deterministic log-linear trend model is estimated separately for the Index of Portfolio Diversification for the three clusters of markets: World, developed, and emerging.

Let Y_t be the logarithm of the index of portfolio diversification for a cluster.

The deterministic log-linear trend model is specified as follows:

$$Y_t = \beta_0+\beta_1 t+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2) \text{ for } t = 1,2,3 \ldots . 20$$

The time variable t represents a deterministic yearly time variable representing the period from 1995 to 2015 and the trend is represented by the line $\beta_0+\beta_1 t$.

The coefficient β_0 represents the intercept and the coefficient β_1 represents the slope. When multiplied by 100, β_1 stands for the percentage change in Y_t per unit of time, that is, by how many percent we expect Y_t to move from one period to the next.

More details on trend estimation are available in Anderson (1971) and Box and Jenkins (1970) among many others.

APPENDIX D

Quadratic deterministic trend models

I investigate the predicted values of the three indices of portfolio diversification by constructing a quadratic deterministic trend model for each index. The same quadratic model is estimated separately for the Index of portfolio diversification for the three clusters of markets: World, developed, and emerging. For each cluster, the model specified as follows:

$$Y_t = \beta_0+\beta_1 t+\beta_2 t^2+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2) \text{ for } t = 1,2,3 \ldots . 20$$

Where, Y_t is the portfolio diversification index for each cluster and t is a deterministic time variable. The time variable t represents a deterministic yearly time variable representing the period from 1995 to 2015 and the trend is represented by the line $\beta_0+\beta_1 t+\beta_2 t^2$.

More details on trend estimation are available in Anderson (1971) and Box and Jenkins (1970) among many others.

APPENDIX E

Trend model forecast

This appendix describes the construction of 5-year trend point and interval forecast values obtained from the recursive estimation of a quadratic trend model. For each cluster, the model is specified as follows:

$Y_t = \beta_0+\beta_1 t+\beta_2 t^2+\varepsilon_t \ldots \varepsilon_t \rightarrow WN(0, \sigma_\varepsilon^2)$ for t = 1,2,3 …. 20

Where, Y_t is the portfolio diversification index for each cluster and t is a deterministic time variable.

For each year, the optimal forecast is:

$E(Y_{t+h}/I_{t+h-1}) = \beta_0+\beta_1(t+h)$, For h = 1….5

Where, I_t is the information set up until period t.

The respective interval forecast of the 95 % confidence interval is:

$E(Y_{t+h}/I_t) - 1.96\sigma_{\varepsilon+h}$, $E(Y_{t+h}/I_{t+h-1}) - 1.96\sigma_{\varepsilon+h}$,

Where, σ_ε is the standard deviation of the white noise term in the quadratic trend model.

More details on trend estimation and forecasting are available in Anderson (1971) and Box and Jenkins (1970) among many others.