The Multiple Dimensions of Asset Allocation: Countries, Sectors or Factors?

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Abstract

Asset allocation has been performed traditionally along country lines. If the balance is shifting towards sectors, then skill in forecasting relative country returns may not be sufficient to ensure investment success. It may lead to suboptimal portfolios. There is growing evidence supporting the emergence of global sectors. We examine this claim, focusing on 19 developed equity markets between 1994 and 2000. We first identify clusters of sectors across countries, using a methodology based on neural networks. Although country stratification remains important, our results suggest a more complex and dual structure across both dimensions. Some clusters correspond to global sectors across regions. In contrast with Heston and Rouwenhorst (1994) seminal model and subsequent research, we develop a framework that allows a large degree of interaction between countries and sectors. We also relax the assumption that country and sector exposures are fixed, thus enabling us to analyze how the two dimensions evolved over time. We perform principal components analysis to identify factors driving returns. By construction, the factors combine both dimensions, geographic and industrial, and are allowed to vary over time. We measure the relative importance of country and sector effects in these factors, and find that sectors have become as important as countries since October 2000. We discuss the implications of these findings for asset allocation. Factors are interpreted as combinations of a limited number of short and long positions. We find that diversification across factors leads to lower risk than diversification across countries or sectors.

JEL Classification: G11,G15, C45

1 Introduction[1]

Managing diversified equity portfolios to achieve a desired risk and return profile requires not only ability to forecast returns and estimate risk, but also to identify an appropriate level of asset stratification. In a traditional top-down framework, portfolio managers first establish positions within asset classes in different countries, and then select industries and eventually individual securities. Implicit in this approach is the belief that country effects constitute the primary determinant of returns - a belief validated by evidence that correlation between country returns is low.[2] But determining the relative and shifting importance of factors that drive the variation in equity returns has been a challenge for practitioners and academics. Which dimension prevails, geography or industry? Should the focus be on regions, global sectors, industry groups or companies? Economic integration and the globalization of trade suggest that countries are becoming increasingly interdependent and that attention ought to be paid to global sectors. If the balance is shifting towards sectors, then skill in forecasting relative country returns may not be sufficient to ensure investment success. It may lead to a misallocation of resources and suboptimal portfolios.

In an early study on the subject, Solnik (1974) established that diversification across countries led to greater risk reduction than diversification across industries. Grinold, Rudd and Stefek (1988) decomposed local excess returns over the period 1983-1988 into components attributable to countries, industries and common factors, including size, yield and volatility. They reported that

[1] We thank F. Owen-Smith for providing the data and S. Cavaglia for details on the methodology. We acknowledge the suggestions of M. Kritzman, J. Armitage, J. Tjornhom and participants at the 2001 Seminar on Asset allocation held at the University of Sherbrooke.

[2] See Solnik (1974), Levy and Sarnat (1970).

"local market factors account for more of the variance than do industry factors in 90% of the months". However, they also noted the increasing role of industries, and that the most important industries were more important than the least important countries. In a seminal study, Heston and Rouwenhorst (1994)[3] proposed a model with dummy variables in order to separate country from industry effects. This is a two-factor model in which a given stock is assumed to have binary exposures. A French utilities firm has a unit exposure its home country and industry, and a zero exposure to other countries and industries. An important feature of the model is that it can be rewritten so as to indicate the potential for outperforming the world index by investing in pure industry portfolio that is country-neutral, or a pure country portfolio that is industry-neutral. The authors show that the country effects dominate and conclude that country diversification is a more effective tool for achieving risk reduction than industry classification. Griffin and Karolyi (1997), using the same model, confirmed that variation in returns was little explained by industrial structure. However, for industries that produce goods traded internationally, the variance of industry factors is relatively large.

But recent studies dispute these results and show that sector effects now dominate. Cavaglia et alia (2000a) revisit HR's model and show that the opportunities for pure industry bets exceed those of countries since early 1997. Industrial diversification provides greater risk reduction than diversification across countries. Cavaglia et alia (2000b) show that cross-country, cross-industry asset allocation dominates country diversification strategies.

L'Her, Sy and Tnani (2001) extended HR's model and incorporated a third factor in addition to country and sector. This global risk factor is measured on

[3] Henceforth referred to as HR.

the basis of size, book-to-market ratio and performance. They find that sectors have become more important than countries since the end of 1999.

The studies previously cited use a framework closely related to HR's factor model. However, we argue that this model present two important drawbacks. First, the model rules out interaction between sectors, and between countries. This is an unrealistic assumption. A chemicals firm in Germany would be exposed only to the chemical industry and to its home country, ruling out richer cross-industry and cross-country effects. Moreover, it assumes that the factor loadings, or exposures, are equal for countries and sectors, and that they are fixed over time. One would expect the importance and composition of factors to change over time. Second, while the analysis of pure country or pure industry tilts is powerful, it leaves a practical question unanswered: Can one invest in such 'pure' portfolios? An investment in a country index encompasses an industry exposure particular to that country. Conversely, investing in a global industry index entails country exposures because not all industries are equally present in all countries. As a result, the practical implications for asset allocation are unclear.

In this study, we attempt to assess the importance of factors combining the two dimensions, countries and sectors and discuss the implications for asset allocation. We show that focusing on factors - or composite assets constructed on relatively few investments in sectors in given countries - leads to diversification benefits far in excess of those provided by country or even sector stratification.

We first show, using correlation heatmaps over the period 1994-2000, that countries still constitute a dominant force. However, we also find strong evidence of global sectors. We use a neural networks technique, Kohonen's (2000) self-organizing maps, to identify covariance clusters. Neurons are trained to identify complex patterns in a multidimensional space, the resulting classification is then projected onto a map so as to preserve the informational content of the covariance matrix. In contrast with traditional clustering methods, the further away clusters are from one another, the higher their degree of heterogeneity. This indicates in itself the diversification potential between groups of assets. We find evidence of a dual structure along countries and sectors. Some clusters are associated with countries or regions, others with sectors such as utilities, basic industries, financials and information technology.

Based on these findings, we then apply principal components analysis to identify factors. In contrast with previous studies, factors are uncorrelated with one another, they combine a geographic and industrial dimension, and their composition changes over time. We use these factors to measure the relative importance of countries and sectors. We use a dummy model as in HR to separate country and sector effects, but our approach differs in that we do not assume 'pure' country or sector exposures. We show that sectors have become as important as countries since October 2000. However, this occurs later than reported in Cavaglia et alia (2000a) because our factors combine the two dimensions.

Finally, we discuss the implications for asset allocation. Factors are interpreted as combinations of long and short positions. We show that constructing composite assets, each involving a limited number of investments in particular sectors across countries, leads to diversification benefits that exceed greatly those obtained by following the traditional approach along country lines, or even global sectors. We focus on minimum variance portfolios. We show that the standard deviation of these optimal portfolios is lower than the ones obtained through diversification across countries, or even sectors. The risk of factor-based portfolios remained stable whereas country-based portfolios became riskier after the Russian default in the fall of 1998, and the risk of sector portfolios increased with the collapse of the technology bubble in March 2000.

2 The Emergence of Global Sectors

2.1 Data

We use data provided by FTSE International. We compute weekly and monthly returns for each sector in a given country from January 1994 until October 2000. The 19 countries in our sample are the following: Australia, Austria, Belgium, Canada, Denmark, Switzerland, Germany, Spain, Finland, France, the United Kingdom, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Sweden and the United States.[4] As in Cavaglia (2000a-b), we concentrate on developed markets although the database covers 48 countries in total. The inclusion of developing markets may bias the analysis. Because they are less integrated with the major markets, they may lead to a mismeasurement of the relative importance of countries and sectors.

The database covers 10 sectors, further subdivided into 39 industries.[5] In this study we focus on the sectors. These are: Resources, basic industries, general industrials, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services, utilities, financials and information technology. We therefore cover in theory 190 portfolios of national sectors. Because not all

[4] We excluded Hong Kong, Singapore, Greece and Portugal because of sparse information.

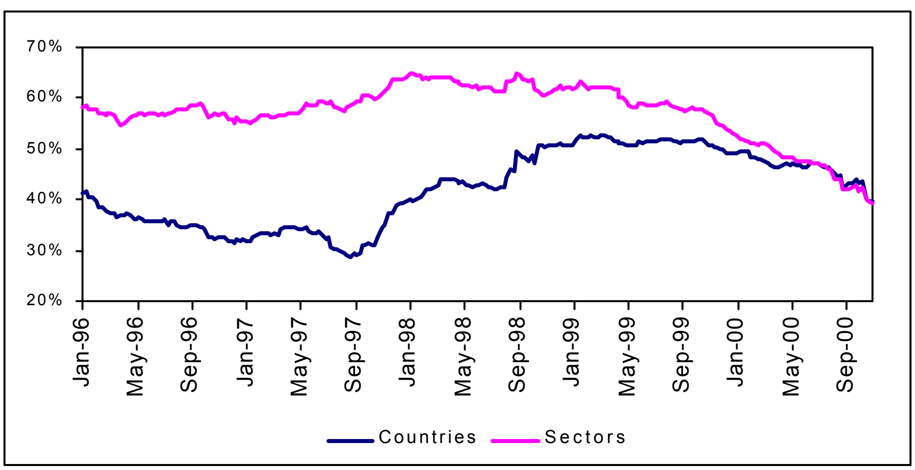
[5] Seet the Appendix for a list of the industries.

sectors are present in the countries, our universe is composed of 154 assets.

2.2 Analysis of Correlations

Which dimension generates the lower correlations, and hence the greater degree of diversification, geography or sector? In Figure 1, we show the evolution of the average sector and country correlations over a rolling window of 104 weeks. Returns for sectors and countries are weighted by market capitalization. For most of the period, country correlations have been lower than sector correlations, justifying a traditional country-based approach to asset allocation. However, country correlations sharply increased after the Asian crisis spread in the fall of 1997 and in the aftermath of the Russian default in August 1998. Since the beginning of 2000 sectors and countries have had similar level of correlations. This implies that the diversification benefit of investing across countries has been erodingsteadily.

Figure 1: Sector and Country Correlations



We now analyze the correlation matrix of weekly USD returns.[6] We present in the Appendix heatmaps of correlations for 10 sectors in the 19 developed markets of the sample. As correlations vary from -1 to +1, the color changes from blue to red. In Figure 2, each box corresponds to a country and is further divided into subcells corresponding to sectors in that country. If country effects dominate, we should observe a concentration of red squares close to the diagonals. In Figure 3, we reverse the two dimensions. Each box now corresponds to a sector and is divided into cells corresponding to countries.

Figure 2 displays strong evidence of country clustering. Correlations are higher close to the diagonals, indicating that sectors in one country tend to be highly correlated with one another. This is true of Australia, Canada, France and Italy, and to a lesser extent of the United States. Sectors in Japan tend to have high and positive correlations with one another, and negative ones with the rest of the world. The United States and Canada are positively correlated, suggesting that they represent a relatively homogeneous North American region.

Do we find evidence of sector stratification? Evidence is less obvious. In Figure 3, the correlations close to the diagonals do not exhibit any clear pattern, except for the basic industries (covering chemicals, construction, forestry and steel) and financials. Information technology also tends to be characterized by relatively high correlations across countries, as well as resources (including mining, oil and gas) to a lesser extent. Utilities are correlated negatively with the other sectors.

[6] We repeated the analysis using local returns. Results are qualitatively similar.

2.3 Identifying Clusters of Assets

Heatmaps are descriptive, they suggest the presence of clusters but do not demonstrate them. To gain a better intuition of the structure of sectors within countries, we need to construct homogeneous clusters of assets. Clusters correspond to groups of sectors across countries that are combined, based on their degree of similarity. One of the most popular methods to construct clusters is the k-means algorithm.[7] The clusters produced are called 'hard' clusters: Any observation either is or is not a member of a particular group. The 'fuzzy k means' method attempts to remedy this, and allows an observation to have a degree of membership in each cluster.[8]

The k-means algorithm and derived procedures suffers from the inconvenience that there is no economic interpretation of the relationship between individual clusters. For example, assume that we identify three clusters, corresponding to European financials, resources worldwide and North America. We know that sectors within each cluster are similar. But the classification fails to provide any intuition as too how close, or similar, the clusters are in relation to one another.

In this section we focus on the covariance matrix. The covariance matrix incorporates information both on risk and co-movement between asset returns, and constitutes the basis on which investors allocate resources in the standard

[7] It identifies k clusters so as to minimize the sum of squared distances to the cluster centers. The algorithm begins by initializing a set of k centers. The observations are assigned to the nearest cluster centers, which are then recomputed iteratively.

[8] It presents two drawbacks. It assumes that the number of clusters is known, and the resulting classification depends on the initial cluster centres which are chosen randomly. See Bezdek, J.C. (1981).

optimization framework.

We have applied a recent methodology based on neural networks, Kohonen's (2001) self organizing maps (henceforth referred to as SOM). The SOM procedure is a method of unsupervised learning where neurons train themselves progressively to recognize patterns. At each iteration, a vector is randomly chosen from the data, distances between that vector and all the centers are computed. The best matching unit is the one closest in the Euclidean sense to the vector. Clusters are then updated. The method is related to the k-means algorithm. However, every time a cluster center is updated, the other clusters in the neighborhood are also updated.

This method is a powerful tool to project and represent complex data onto a two-dimensional grid, and preserve informational content.[9] The final output consists of a map of units connected to adjacent ones. The geometric organization of the map has a valuable economic interpretation: Cells that are spatially close to one another present similar patterns. Units located further away are increasingly dissimilar. Applied to financial assets, the map provides a visualization of their diversification potential.

The self-organizing map obtained from the covariance matrix of weekly USD returns is presented in Figure 4. The topology of the matrix is projected onto a 13×5 map of hexagonal neighboring cells. Different colors are used to separate 14 clusters.[10]

Individual countries remain important but we find evidence of regions and

[9] "It compresses information while preserving the most important topological and/or metric relationships of the primary data elements", Kohonen (2001, page 106).

[10] The number of clusters was found by minimizing the Davies Bouldin (1979) criterion. The DB index weighs intra to inter cluster distance.

global sectors. Japan constitutes clearly its own cluster, located on the top left handside. Below, we find a cluster grouping together Australia and New Zealand. However, this Australian cluster is surrounded cells corresponding to the resources and basic industries sectors of Canada and the UK - an intuitive feature as Australia and Canada are to a certain extent commodity-linked economies. Below again, we find a cluster associated with the USA and Canada. Italy also constitutes a well-defined group.

In contrast with the heatmaps of correlations discussed above, we find compelling evidence of sector clustering. At the bottom on the left, a group of cells group together information technology (i.e. sector 90) and immediately above, non-cyclical services (including telecommunication services). The group to its right cells represents basic industries in Sweden, Norway and Finland. On the top left corner, we find utilities (i.e. sector 70). Finally, some units on the middle part of the map may be interpreted as a global and industrially-diversified European cluster.

We notice that utilities are located far away from information technology, and that Japan (and to a lesser extent Australia and New Zealand) are distant from European sectors. Overall, the map suggests a complex dual structure across countries and sectors.

3 Identifying Factors Driving Equity Returns

3.1 Methodology

The preceding analysis suggests that the two dimensions, geographic and industrial, need to be considered simultaneously for asset allocation. Both countries and sectors drive returns. However, two difficulties arise. First, it is delicate to disentangle the two effects - if only because they vary in relation to one another over time. Second, making investment decisions over more than 150 assets is likely to be impractical. It is well-known that applying the standard Markowitz mean-variance optimization framework would only lead to optimize over noise or estimation errors.

The objective is therefore double: 1) Reduce the number of assets under consideration, and 2) Allow the relevant 'factors' to combine the two dimensions without imposing a view. In order to do so, we apply Principal Components Analysis, a method of linear transformation which uses the information contained in the covariance matrix to identify components so that they explain the maximum amount of total variance. The principle is to reduce the $p \times p$ covariance matrix S to a diagonal matrix L as follows:

$$U'SU = L$$

The diagonal elements of L are the eigenvalues (or characteristic roots) of the covariance matrix. The columns of U constitute the eigenvectors, or factors. Each factor is defined so as to maximize the variability that is not captured by the preceding factor. Factors are therefore uncorrelated with each other. The factors that most contribute to variability are associated with the largest eigenvalues, that is to say, they are classified by decreasing amount of total variance explained. The trace of S (i.e. the sum of the variances on the diagonals of S) is equal to the sum of the eigenvalues.

We have performed a decomposition into principal components of the covariance matrix of weekly USD returns for the period 1994 to 2000. We obtain a matrix L with 142 eigenvalues. An important question is to determine the number of factors to retain. There is no universally accepted answer to the problem. We have applied a number of methods and they all disagree. The SCREE plot[11] suggests that only 5 factors should be retained. The Broken Stick[12] retains the first 12 factors, but they account for only 55% of the total variance which is too little. The Average Root[13] rule suggests 32 factors. Finally, we retained Velicer's partial correlation procedure[14] that calls for 20 factors. They represent 65% of the total variance.

3.2 Comments

We present a heatmap of the first 20 factors in Figure 5a. The first factor has positive loadings with all countries and sectors. It can be interpreted as the world market factor. We find clear evidence of regional stratification, a result in line with our findings based on the self-organizing map. Japan and Italy appear as factors 3 and 4 respectively. The 5th factor corresponds to Australia and New Zealand, suggesting that they represent a region on their own. The USA and Canada are associated with factor 7, with negative yet high loadings. The 17th factor seems to correspond to Finland. We find weaker evidence of sector clustering. In Figure 5b, we reorder the cells so that they correspond to sectors. The second factor seems to be associated with information technology.

[11] One plots the eigenvalues and identifies at which point there seems to be a break.

[12] If one breaks a line segment of unit length into p segments, the expected length of the kth longest piece is $g_k = \frac{1}{p}\sum_{i=k}^{p}\frac{1}{i}$. One retains the factors as long as the proportion explained by each is larger than the corresponding g_k.

[13] One retains the factors whose eigenvalues exceed $Trace(S)/p$ which is the size of the average root.

[14] Based on the computation of partial correlations with one or more factors removed. See Jackson (1991) page 48.

In order to facilitate visual interpretation, we have performed a Varimax[15] rotation of the factors. After rotation (see Figure 6a), we find the surprising result that the first factor, accounting for the greatest percentage of explained variance, corresponds to Sweden and Finland. This result may be explained by the fact that our analysis includes a period characterized by strong growth and volatility in the telecommunications and information technology sectors. However, this result seems to be sensitive to the frequency at which we calculate returns. We performed the same analysis for monthly returns and found that the most important factor was North America, an intuitive result.

After rotation, we find again country-specific factors. Japan, Italy and Australia appear respectively in factors 3, 4 and 5. We find factors associated with New Zealand, Norway and Denmark. Some principal components are characterized not by negative exposures. The 7th factor has negative loadings for the USA and Canada. Reordering the factors by sector (see Figure 6b), we find some evidence of sector clustering. Factor 6 has negative loadings for non-cyclical services, factor 7 for financials and factor 10 for resources.

Principal components have an economic interpretation. They can be viewed as a *combinations of weights*, positive and negative, in the same sense that a hedge fund portfolio may be composed of long and short positions. To illustrate this view, we consider factors 2 and 3 in Figure 6c. After rotation, these factors correspond respectively to 'Sell Germany, the Netherlands, Switzerland and Belgium', and 'Buy Japan'. The heatmap at the top represents the factors weights. We have plotted below the histogram of weights. Many cells in factor 3 have weights close to zero. The weights for Japan are highly positive, which

[15] The objective is to produce a new set of independent vectors, with as little overlap with one another as possible. See Jackson (1991), page 161.

is reflected in the positive skewness of the loadings distribution. By contrast, factor 2 has many more negative weights, interpreted as short positions.

For practical purposes, these factors may therefore be viewed as a combination of long positions (positive loadings) and short ones (negative loadings). These factors tend to have relatively few large positions, in absolute terms, so that they can replicated closely by investing in a limited number of sectors across countries.

3.3 Measuring the Relative Importance of Countries and Sectors

Heston and Rouwenhorst (1994) decompose stock returns in order to separate the country from the sector effect. The residual components corresponds to company-specific factors uncorrelated with country and sector effects. This framework, which constitutes the basis for the majority of studies devoted to the topic, consists in estimating cross-sectional regressions of returns[16] on a set of dummy variables. The model is expressed as follows, for J industries and K countries:

$$R_i = \alpha + \sum_{j=1}^{J} \beta_j I_{ij} + \sum_{k=1}^{K} \gamma_k I_{ik} + \varepsilon_i \tag{1}$$

where R_i is the return for company i, the constant α represents a global factor common to all companies, I_{ij} is a dummy variable equal to 1 if the firm belongs to industry j and 0 otherwise, I_{ik} is another dummy equal to 1 if the firm is located in country k and 0 otherwise, and ε_i is a firm-specific disturbance term.

[16] The estimation may also be performed on value-weighted indexes of securities. See Cavaglia (2000a).

Because of a firm belongs by definition to a country and a sector, multicollinearity in the regressors is an issue. The solution is to measure the effects against the average of the firms in the sample. This is done by imposing two constraints so that the capitalization-weighted sum of country and sector dummies are both equal to 0.

The appeal of this methodology is that the coefficients possess a natural economic interpretation. The constant is equal to the return of the capitalization-weighted world portfolio. The estimates of β_j and γ_k are interpreted as 'pure' industry and 'pure' sector returns. The sum $\alpha + \beta_j$ represents the return on a geographically-diversified portfolio in sector j, while $\alpha + \gamma_k$ represents the return on a industrially-diversified portfolio in country k.

This simple yet powerful model presents two major drawbacks. First, exposures to a particular country and sector, not only remain fixed over time, they may take only two values, 0 or 1. This model rules out interaction between sectors, and between countries - a highly unrealistic assumption. A chemicals firm in Germany would be exposed only to the chemical industry and to its home country, ruling out richer cross-industry and cross-country effects. Second, it may be argued that there is no such thing as a 'pure' country or a 'pure' sector portfolio. Countries differ in their industrial structure, and all sectors are not present in all countries. In other words, the analysis of pure country or sector indices is interesting for analytical purposes, but it is impossible as yet to take advantage of the higher returns of sector-based portfolios.[17] In the absence of financial products offering the opportunity to invest in a country-neutral or industry-neutral portfolios, the HR model lacks practical implications for in-

[17] Cavaglia (2000a) shows that 'since 1997 the return opportunities from industry tilts have dominated those emanating from country tilts'.

vestors.

To overcome these limitations, we propose to focus on factors, defined as principal components. This is to recognize the fact that the factors driving returns are not structured simultaneously across the two dimensions, geography and sector, and vary over time.

The decomposition of the covariance matrix of returns into principal components in the preceding section was based on the entire sample, 1994-2000. In order to measure the relative importance of countries and sectors, we consider a rolling two-year window of weekly returns and perform principal components analysis on the corresponding covariance matrix. We retain 20 factors.

Although the resulting factors combine the two dimensions by construction, it is still useful to separate the country from the sector effect in order to contrast our results with the literature. For each factor ($f = 1, ...20$), we first perform the following regressions[18]:

$$\begin{aligned} Z_f &= \alpha + C\beta_f + S\gamma_f + e_f \qquad (2) \\ &= \alpha + (c_{f1}\beta_{f1} + ...c_{f19}\beta_{f19}) + (s_{f1}\gamma_{f1} + ...s_{f10}\gamma_{f10}) + e_f \end{aligned}$$

with Z_f^t the f-th vector of the matrix of principal components, C and S are matrices of dummy variables and e_f is an error term. C and S exhibit perfect multicollinearity. In order to estimate the model, we minimize the square of the

[18] We drop the time index t. We have 19 countries and 10 sectors in the sample.

errors e_f^2 and impose two restrictions:[19]

$$\sum_{k=1}^{K=19} w_k \beta_{fk} = 0 \quad (3)$$
$$\sum_{j=1}^{J=10} v_j \gamma_{fj} = 0 \quad (4)$$

where w_i and v_j are the market capitalizations weights of respectively country k and sector j.

The second step is to compute the weighted average of the coefficients associated with the country dummies and the sector dummies, by multiplying them by the percentage of the variance explained by each factor. We then calculate the mean of these values across the 20 regressions. We obtain two numbers summarizing the strength of the sector and country effects. The procedure is repeated every week to obtain weighted indexes.

In Figure 7, we present the two indexes representing how country and sector effects evolved over time. The indexes have been normalized, by setting the country index to 100 at the beginning of the sample. Countries constituted the dominant force but their importance steadily decreased. We observe a structural break in October 1998, in the aftermath of the Russian default. The importance of sectors increased greatly after this date and have become as important as countries since October 2000. Cavaglia et alia (2000a) reported a similar result occurring as early as 1997. The timing difference is explained by the fact that we allow richer interactions across countries and sectors in that our factors combine the two dimensions.

[19] The model can also be estimated via ordinary least squares by dropping the last column of the dummy matrices and imposing a set of linear restrictions on the coefficients.

4 Using Factors for Asset Allocation

The preceding results suggest that it becomes increasingly important to take into account the emergence of global sectors, while recognizing the importance of countries. Focusing on one dimension is probably insufficient to achieve portfolio efficiency.

How can the two dimensions be taken into account simultaneously to invest across countries in different sectors? We use the decomposition into principal components developed above. First, we consider the 20 most important factors. Each factor may be interpreted as a combination of long and short positions of sectors across countries. We normalize each factor so that the sum of loadings equals one.

Each factor has 154 positions. In order to reduce the size of the investment universe, we focus on the N most positive and N most negative weights. Each factor is thus reduced to a combination of $2N$ investments. We compute weighted returns using these loadings and obtain historical returns for the 20 composite assets.

We then perform the following experiment on a rolling window basis[20]. We calculate the optimal portfolio weights so that historical risk is minimized.[21] We conduct the exercise by optimizing successively across three different asset classes: 1) 19 developed countries indexes, 2) 10 global sectors indexes, and finally, 3) the 20 composite assets defined above. We repeat this experiment for $N = 5, 10$ and 20 assets, so that each factor is composed of 10 to 40 positions.

This experiment is performed out-of-sample, we do not use any information

[20] Returns are annualized. We consider a two-year period, corresponding to 104 weeks.

[21] We focus on minimizing risk rather than maximizing expected utility because we do not have a satisfying model to estimate expected returns across sectors and countries.

that was not available at the time of the optimization. Every week[22] we compute optimal weights by using the rolling two-year covariance matrix of historical returns. We then calculate the return that would have been realized in the following week. The procedure is repeated every week. Finally we obtain 3 series of realized returns, from January 1996 until October 2000.

We plot in Figure 8 the annualized risk of the returns generated by the 3 strategies. We use a 48 week moving window to compute standard deviations. Three remarks can be made. First, diversification across sectors leads to lower risk than diversification following country lines. The two strategies would have generated similar standard deviations since March 2000. The risk of country-based portfolios increased significantly after the Russian default in August 1998 and diminished to pre-crisis levels only a year later. We observe an increase in the risk of sector-based portfolios after March 2000, coinciding with the collapse of the dot-com and technology sectors. Second, increasing the number of positions from $N = 5$ to 20 for the composite assets increases the portfolio standard deviation. Two opposite effects explain this phenomenon. On the one hand, the average correlation between composite assets diminishes as the number of positions increases. On the other hand, as more diverse assets are selected to construct the composite assets, their variances increase, and hence the variance of the optimal portfolio. This latter effect dominates the former.

Finally, even for a relatively large number of assets (i.e. $N = 20$), the standard deviation of the minimum variance portfolio is *always lower* than the one obtained using global sectors. Also, the standard deviation obtained using factors remained relatively stable.

[22] Most managers would optimize at a monthly or quarterly frequency. However, we have a short data sample.

5 Conclusions

A number of portfolio managers still make investment decisions by focusing first on countries or regions. Heston and Rouwenhorst (1994) justified this traditional approach, showing that country diversification is a more effective tool to reduce risk than industry stratification. However, there is growing evidence that global sectors now constitute an important driver of equity returns. If this trend is indeed underway, focusing solely on countries or regions may lead to a misallocation of resources and suboptimal portfolios. Recently, Cavaglia et alia (2000a) revisited HR's two-factor model and showed that the opportunities for industry tilts exceeded those of country tilts as early as 1997.

In this study, we argue that reality is likely to be in the middle, and that the relevant framework to assess the importance of the two dimensions should not be static. The reference model used in most studies devoted to the topic presents two important drawbacks. First, exposures to a country or a sector, not only remain fixed over time, they may take only two values, 0 or 1. In effect, this model rules out richer interactions between sectors, and between countries - a questionable assumption. Second, it leaves a practical question unanswered: Can a portfolio manager take advantage of the higher returns of sector-based portfolios? It may be argued that there is no such thing as a 'pure' country or a 'pure' sector portfolio. Countries differ in their industrial structure, and all sectors are not present in all countries. The analysis of pure country or sector indexes is interesting for analytical purposes. But in the absence of financial products offering the opportunity to invest in a country-neutral or industry-neutral portfolios, the HR model lacks practical implications for investors. A country index encompasses an industry exposure particular to that country, and investing in a sector index entails a country exposure.

We propose an approach to asset allocation based on factors. Factors are obtained through the decomposition of the covariance matrix into principal components. By construction, they *combine simultaneously* the two dimensions. This approach is motivated by an analysis of clusters of sectors across countries. We find evidence of a complex dual structure: Countries remain important but the emergence of global sectors is increasingly clear. Factors possess an intuitive financial interpretation: They can be viewed as composite assets combining long and short positions. They are constructed using a limited of investments across countries and sectors.

We find three important results for global asset allocation. First, sectors have become as important as countries since October 2000. This result is in line with Cavaglia et alia (2000a) but occurs later because we focus on composite factors whereas they constructed pure country and sector indexes. Second, a factor-based approach involving a limited number of positions appears to generate superior diversification benefits than the traditional approach along country lines, or even global sectors. We focus on minimum variance portfolios and compute realized returns out-of-sample. The standard deviation of these optimal portfolios is lower than those obtained by diversifying across countries or sectors. The risk of factor-based portfolios remained relatively stable whereas country-based portfolios become much riskier after the Russian default in the fall of 1998, and the risk of sector portfolios increased with the collapse of the dot-com and technology bubble in March 2000.

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6 Appendix

6.1 List of Sectors and Industries

Table 1: List of Sectors and Industries

Sectors		Industries	
0	Resources	4	Mining
		7	Oil & Gas
10	Basic Industries	11	Chemicals
		13	Construction & Building Materials
		15	Forestry & Paper
		18	Steel & Other Metals
20	General Industrials	21	Aerospace & Defence
		24	Diversified Industrials
		25	Electronic & Electrical Equipment
		26	Engineering & Machinery
30	Cyclical Consumer Goods	31	Automobiles
		34	Household Goods & Textiles
40	Non-Cyclical Consumer Goods	41	Beverages
		43	Food Producers & Processors
		44	Health
		46	Packaging
		47	Personal Care & Household Products
		48	Pharmaceuticals
		49	Tobacco
50	Cyclical Services	51	Distributors
		52	General Retailers
		53	Leisure, Entertainment & Hotels
		54	Media & Photography
		56	Restaurants & Pubs
		58	Support Services
		59	Transport
60	Non-Cyclical Services	63	Food & Drug Retailers
		67	Telecommunication Services
70	Utilities	72	Electricity
		73	Gas Distribution
		78	Water
80	Financials	81	Banks
		83	Insurance
		84	Life Assurance
		85	Investment Companies
		86	Real Estate
		87	Speciality & Other Finance
90	Information Technology	93	Information Technology Hardware
		97	Software & Computer Services

Figure 2: Heatmap of Correlations - Weekly Returns (1994-2000)

Ordered by Country

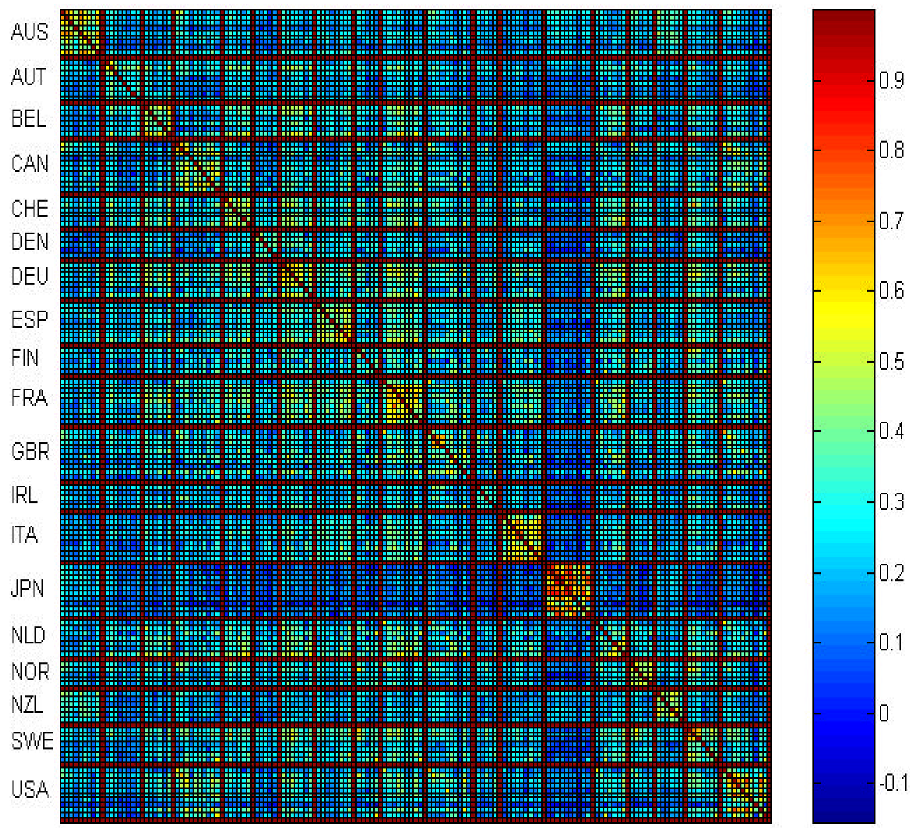

Figure 3: Heatmap of Correlations - Weekly Returns (1994-2000)

Ordered by Sector

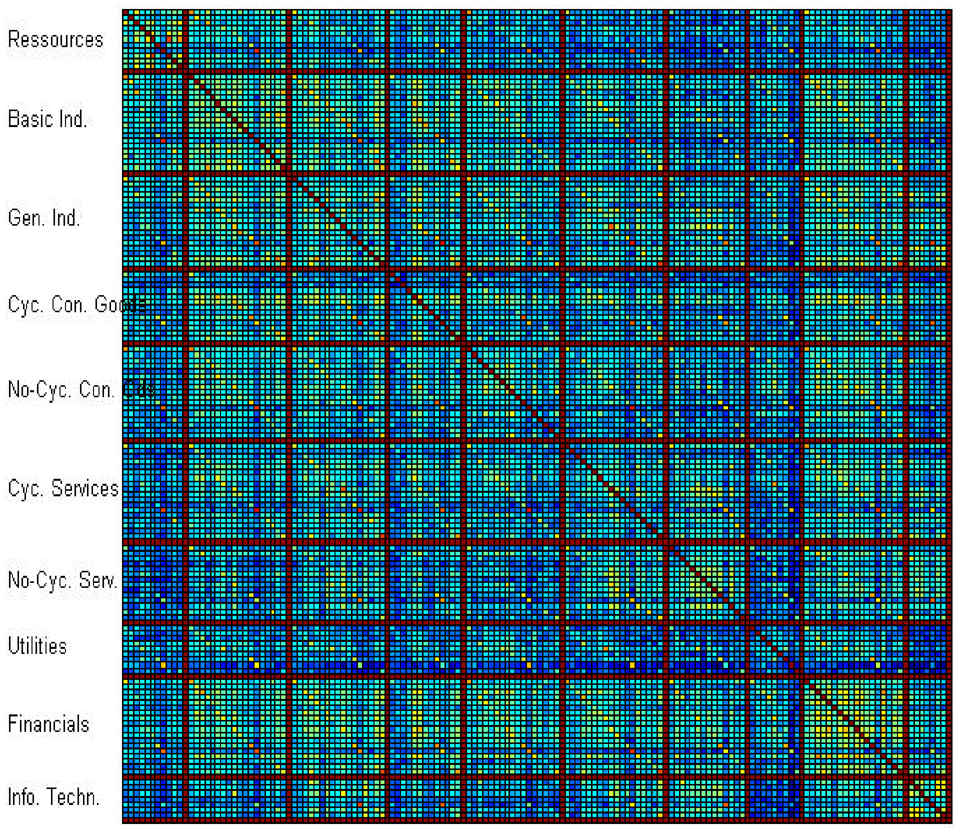

Figure 4: Self-Organizing Map - Covariance of Weekly Returns 1994-2000

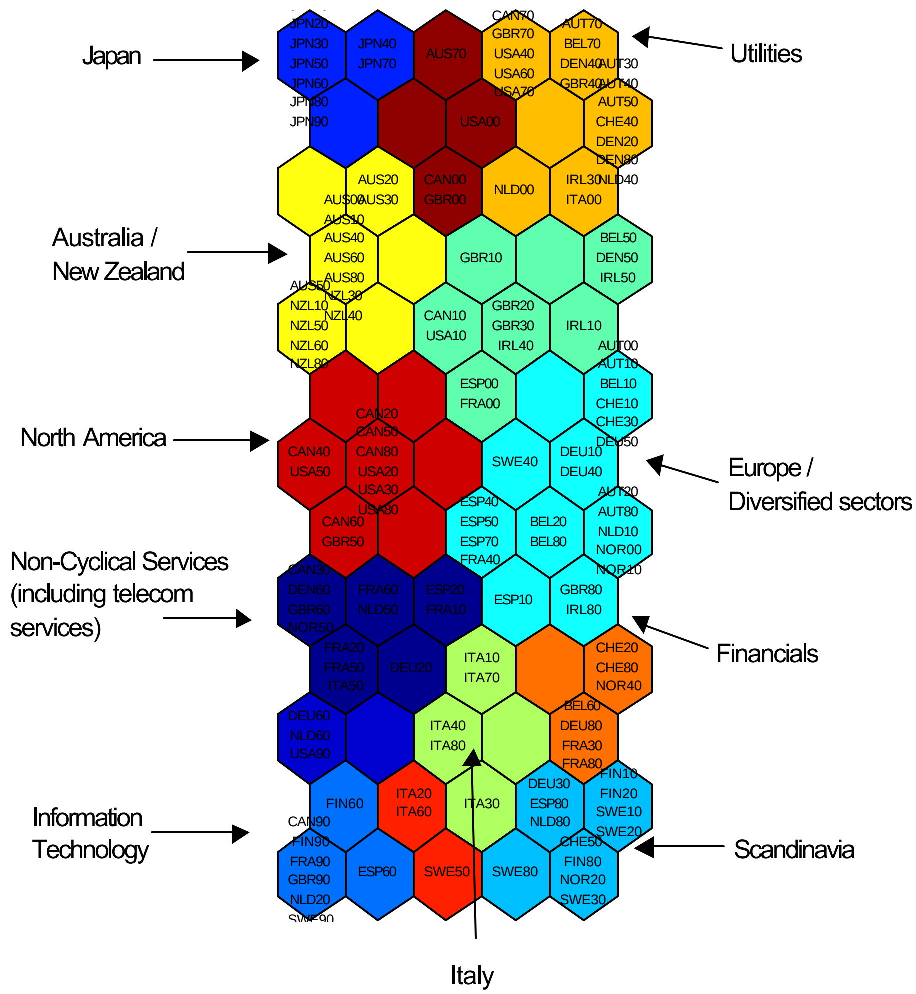

Figure 5a: First 20 Factors Ordered by Country

Based on the Covariance of Weekly Returns 1994-2000

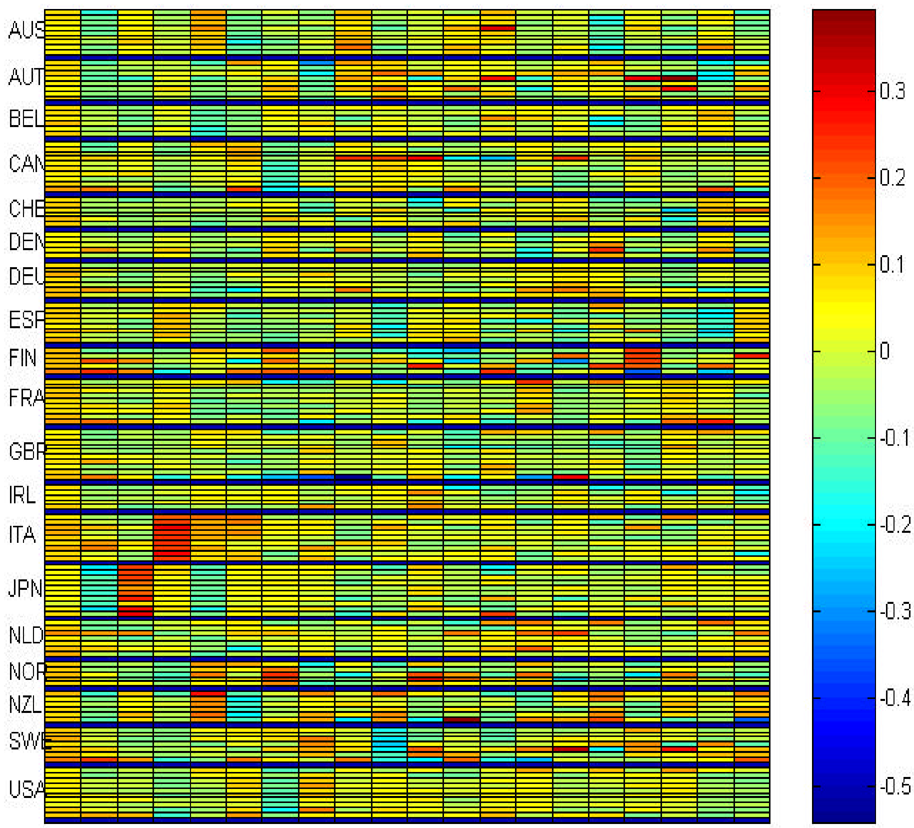

Figure 5b: First 20 Factors Ordered by Sector

Based on the Covariance of Weekly Returns 1994-2000

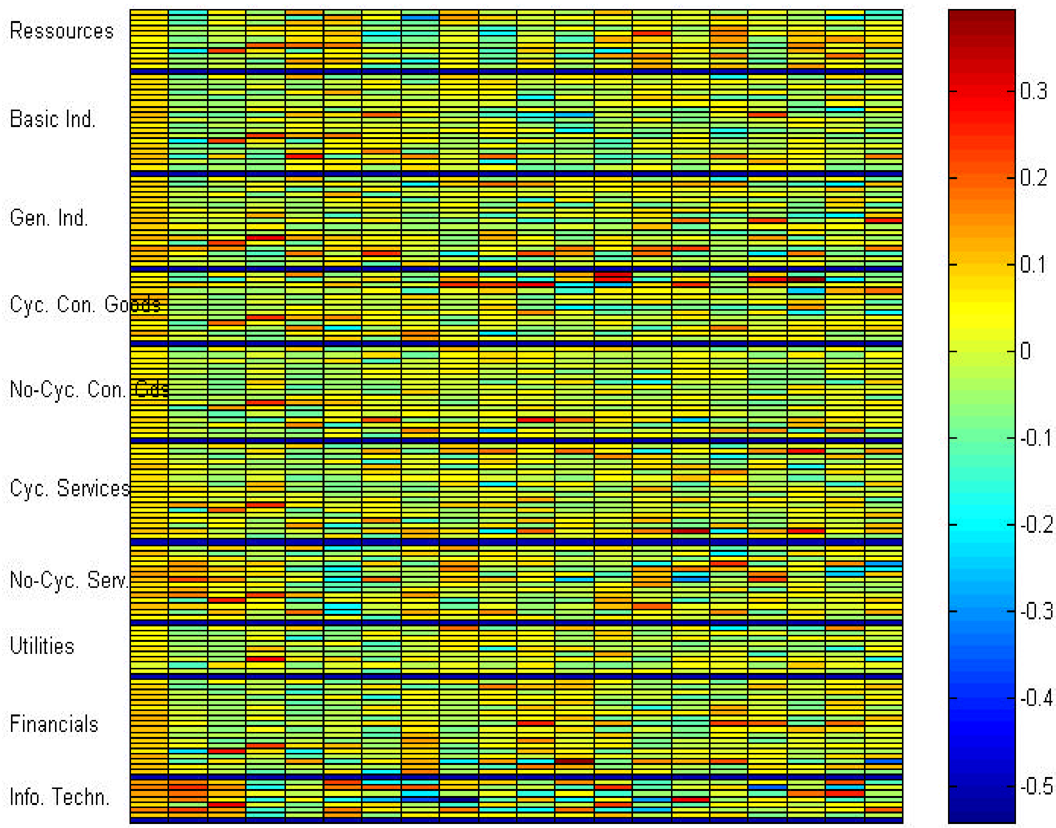

Figure 6a: First 20 Factors Ordered by Country - After Varimax Rotation

Based on the Covariance of Weekly Returns 1994-2000

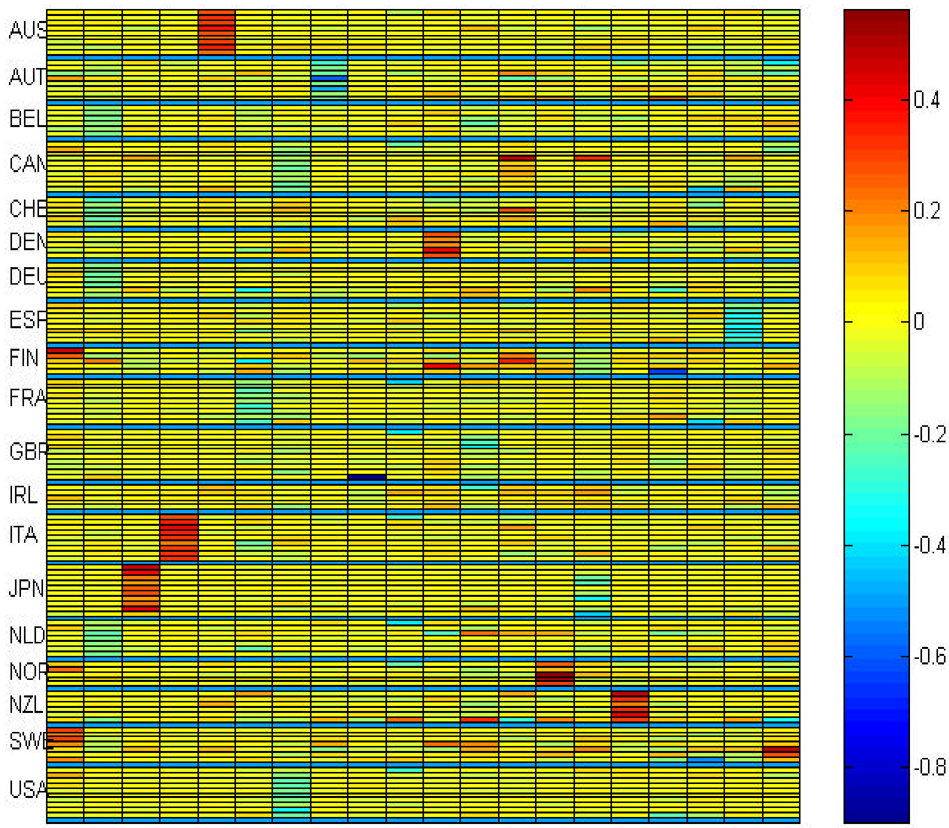

Figure 6b: First 20 Factors Ordered by Sector - After Varimax Rotation

Based on the Covariance of Weekly Returns 1994-2000

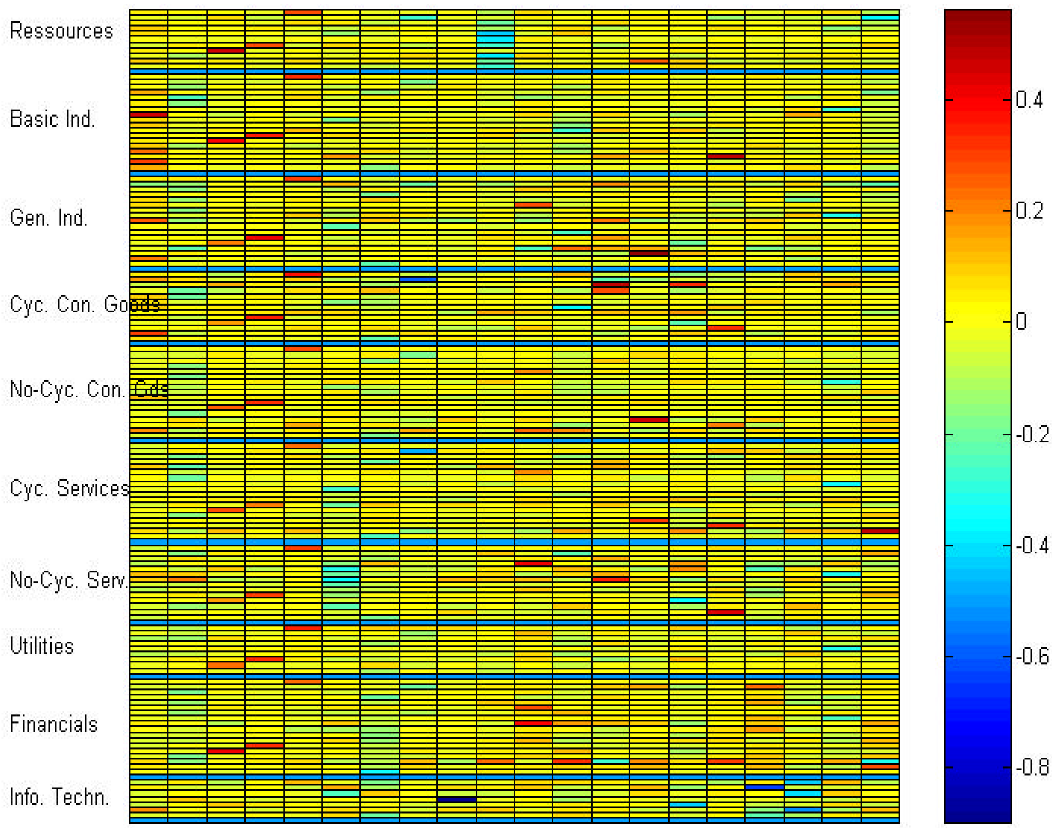

Figure 6c: Interpretation of Factors

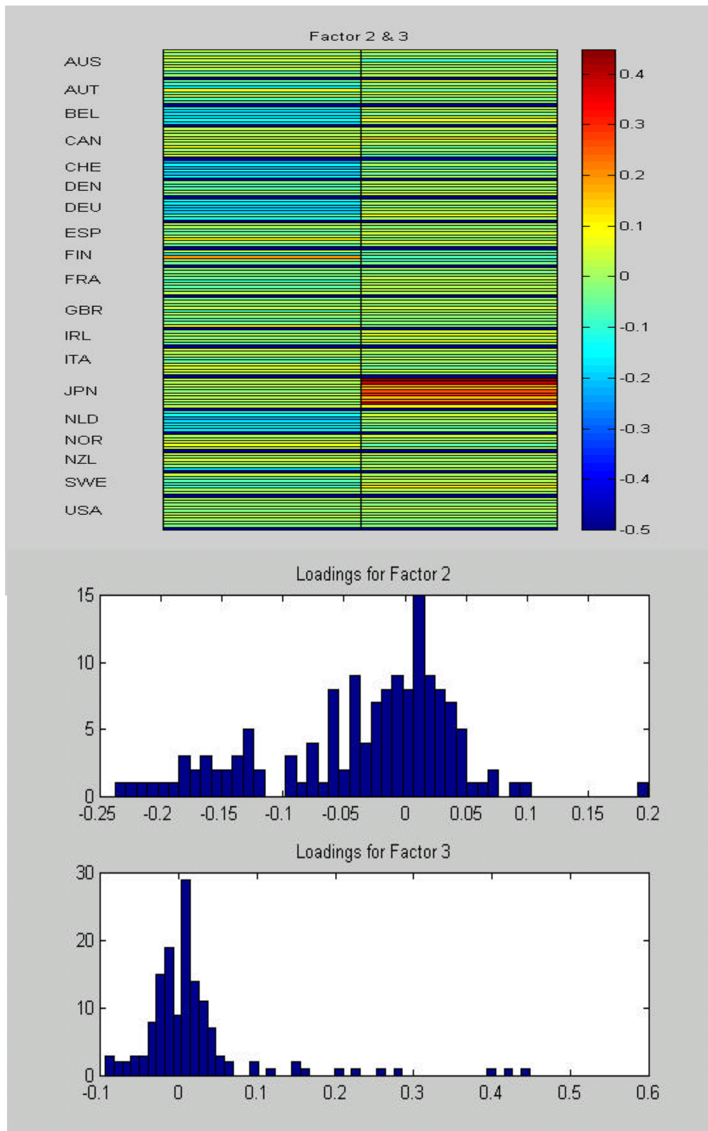

Figure 7: Relative Importance of Countries versus Sectors

(based on 20 factors)

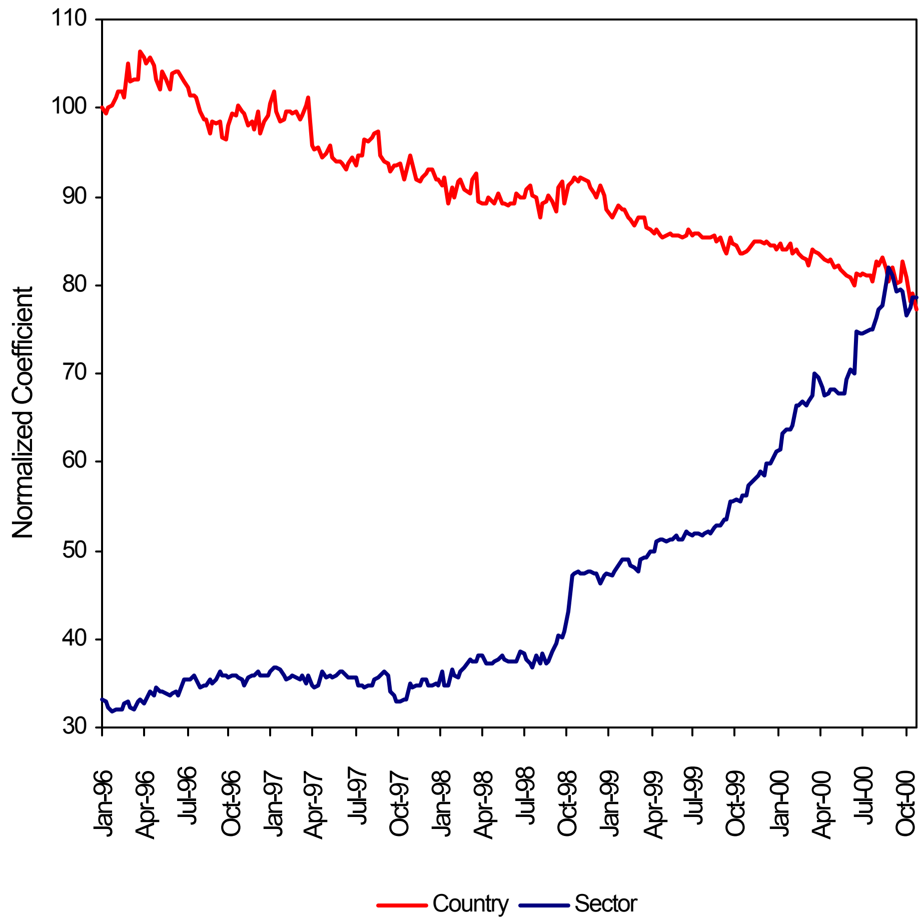

Figure 8: Standard Deviation of Minimum Variance Portfolios

(using 20 factors and a 48 week moving window)