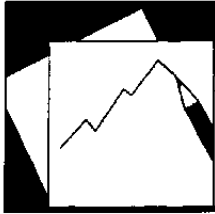


Working Paper

INTERNATIONAL MONETARY FUND



WP/03/52

IMF Working Paper

Country and Industry Dynamics in Stock Returns

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IMF Working Paper

Research Department

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March 2003

Abstract

<p>The views expressed in this Working Paper are those of the author(s) and do not necessarily represent those of the IMF or IMF policy. Working Papers describe research in progress by the author(s) and are published to elicit comments and to further debate.</p>
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A perennial question in international finance is to what extent stock returns are influenced by country-location, as opposed to industry-affiliation, factors. This paper develops a novel methodology to measure these effects, in which portfolios mimicking “pure” country and industry factors are first constructed and their joint dynamics then modeled as regime-switching processes. This methodology is applied to international firm level data over the period 1973-2002. Well-defined periods of high and low stock return volatility are identified, and the relative contribution of industry and country factors is shown to vary significantly across states. Implications for portfolio diversification possibilities are discussed.

JEL Classification Numbers: C1, G11, G15

Keywords: Diversification, Risk, Volatility States, Regime Switching, International Financial Markets

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I. INTRODUCTION

A much-debated question in international finance is the extent to which firms' stock returns are influenced by country-location as opposed to industry-affiliation factors. Following Heston and Rouwenhorst (1994, 1995), a large literature has sprung up in recent years trying to measure the relative importance of these two effects. The standard approach consists of estimating cross-sectional regressions of individual firms' stock returns on a set of country and industry dummies, so that the coefficients on the dummies are interpreted as "excess-returns" associated with country or industry-affiliation relative to a perfectly diversified world portfolio. By and large, this literature has concluded that the country factor explains most of the cross-sectional variation in stock returns (Beckers et al., 1996; Grifins and Karolyi, 1998; Rouwenhorst, 1999; Serra, 2000), though its importance appears to have been waning in recent years relative to that of the industry factor, likely reflecting global financial integration (Baca et al., 2000; Brooks and Catão, 2000; Cavaglia et al. 2000).

Extant results have been based on the sum of the absolute coefficients on the industry and country dummies or, more usually, on the time-series variance of those coefficients in each cross section computed over arbitrarily specified (fixed or rolling) time windows. Implicit in this approach is the assumption that the factors driving country and industry-affiliation effects either remain constant over time or, at most, change very gradually. However, there are reasons to expect otherwise. For instance, policies that influence country risk are well-known to display discrete changes, and the emergence of new technologies (such as information technology) can radically change the dynamics of the data generation process behind industry-affiliation effects. Indeed, the presence of such discrete and persistent changes is a well-known possible cause of business cycle asymmetries in macroeconomics (Hamilton, 1989) and also a much acknowledged source of non-linearities in asset risk and volatility clustering in financial data (Pagan and Schwert, 1990; Harvey, and Zhou, 1993). This suggests the need for greater flexibility in modeling the dynamics of country and industry effects.

This paper advances an alternative, dynamically richer framework to model such effects. It proposes a two-stage estimation method where in the first stage cross-sectional regressions are used to form country and industry portfolio returns. The dynamics of the returns on the various country and industry portfolios are then modeled as regime-switching processes in a second stage. The benefits of using cross-sectional regressions to form country and industry portfolios is twofold: first, it can be applied to large unbalanced panels; and second, it reduces the number of time-series to manageable dimensions that permit the modeling of their joint dynamics as regime-switching processes, which are likely to provide a more accurate characterization of the (possibly nonlinear) dynamics of common factors in portfolio returns.²

² See Timmermann (2000) and Perez-Quiros and Timmermann (2001) for a discussion of this point.

The proposed two-stage approach builds on a long tradition in empirical finance, following the Fama and MacBeth (1973) method for testing asset pricing models. In their study, cross-sectional regressions are used to estimate risk premia on a variety of risk factors (including market exposure) in a first stage, whereas time-series averages and risk-premium standard errors are used to test their statistical significance in a second stage. The main difference between the Fama-MacBeth method and our method lies in the second-stage regressions where we do not simply consider the unconditional average returns on the various country and industry factors but model their joint dynamics. Specifically, the time-series model we consider allows for different “regimes” in portfolio returns, where each industry or country has a fixed (time-invariant) mean and variance within a particular regime. By allowing these parameters to vary across regimes and assuming that next period’s regime is never known in advance, the model is capable of capturing complex country and industry factor dynamics which may have been overlooked in previous studies.

There are several advantages to our approach. By allowing the underlying volatilities and correlations to be driven by a discrete state variable that can switch from one period to the next, we achieve more of what Solnik and Roulet (2000) refer to as an “instantaneous measure” of the correlation and volatility levels. Furthermore, to capture the possibility that risk characteristics of the separate country, industry and global component change at different frequencies, we allow shifts in these components to be driven by different discrete state variables displaying different degrees of persistence.

Using this framework, our paper addresses the following questions. First, does the “stylized fact” that country factors dominate industry-affiliation effects in fact hold uniformly over time and across economic states? Or, does it result from a type of dynamic misspecification stemming from the use of the standard single-regime linear model? Second, how much of the “excess” stock returns are explained by “pure country” and “pure industry” factors within each state (if there is more than one)? Third, what is the typical “persistence” of such states and what is the strength of the various individual country and industry return correlations within them? Fourth, how much does the global return component (which could be loosely viewed as a common “world” business cycle factor) vary over time and across economic states and how does this affect the correlations between country- and industry portfolios? Answers to these questions obviously have important implications for international risk management.

The main results are as follows. First, we find very strong evidence of nonlinear dynamic dependencies in both industry and country returns, suggesting that the dynamic “mixtures of normals” model underlying the Markov-switching approach offers many advantages in terms of modeling global stock returns. In particular, specification tests reject (at the 1 percent significance level) the null hypothesis of a single state model for 10 of the 13 advanced countries comprising our sample, and for 10 out of 11 industries (using the standard FTSE classification). Instead, we find evidence of two distinct states characterized by very different volatilities of stock returns, with the global high volatility regime tending to be less persistent than the low volatility regime. Second, once we model the nonlinear dynamics jointly across blocks of industry portfolios, we find a clear common nonlinear

dynamic component from the industry return series, with industry volatility increasing relative to country volatility from the late 1990s. This points to the growing prominence of global industry effects alluded to in the recent literature. Third, we identified high and low volatility regimes in the vast majority of individual country portfolios. However, we could not identify similar states in the common time-series component in the volatility of the country-return series, suggesting that country effects continue to be more heterogeneous than industry effects.

The remainder of the paper is structured as follows. Section II lays out the econometric methodology, while section III discusses the data. Empirical results are reported in sections IV and V. Section VI considers implications for global portfolio diversification. Section VII summarizes the main findings.

II. ECONOMETRIC METHODOLOGY

While an obvious approach to estimating the dynamics of country and industry factors in stock returns would be to estimate the various country and industry parameters jointly in a dynamic panel, this is not a feasible option when using large cross-sections of firm level data. Such panels comprise thousands of individual stock returns and tend to be highly unbalanced due to the fact that some firms die while others are “born” at some point within any reasonably long time series on stock return data.

Here we present an alternative approach to this problem which does not entail losing information contained in the time series dynamics of individual country or industry stock return series nor in the whole cross-sectional dimension of the data. Specifically, we propose a two-stage approach where, in the first stage, we follow Heston and Rouwenhorst (1994, 1995) and extract the industry and country returns for a given time period through cross-sectional regressions in which each firm’s stock returns is defined as:

$$R_{ijt} = \alpha_t + \beta_{jt} + \gamma_{kt} + \varepsilon_{it}, \quad (1)$$

where R_{ijt} stands for the return at time t of the i^{th} firm which belongs to the j^{th} industry and the k^{th} country, α_t is a global factor common to all firms, β_{jt} is an “excess” return owing to the firm’s belonging to industry j , γ_{kt} is an “excess” return associated with the firm’s location in country k , and ε_{it} is an idiosyncratic firm-specific factor. Assuming that there are J industries and K countries, equation (1) can be written as:

$$R_{ijt} = \alpha_t + \sum_{j=1}^J e_{ij\beta} \beta_{jt} + \sum_{k=1}^K e_{ik\gamma} \gamma_{kt} + \varepsilon_{it}. \quad (2)$$

Here $e_{ij\beta}$ is a dummy variable defined as 1 for the i^{th} firm’s industry and zero otherwise, while $e_{ik\gamma}$ is a dummy defined as 1 for the i^{th} firm’s country and zero otherwise.

Since each firm can only belong to one industry and one country at a time, the various industry dummies in (2) will be orthogonal to each other within the cross-section. Likewise, the various country dummies will also be orthogonal to each other. However, equation (2) cannot be estimated as it stands because of perfect multicollinearity among the regressors. This is because every company belongs to both an industry and a country, whereas the industry and country effects can only be measured relative to a benchmark. To resolve this identification issue, we follow the literature in imposing the restriction that the weighted sum of industry and country effects equals zero at every point in time, so that the industry and country effects are estimated as deviations from the intercept α :

$$\sum_{j=1}^J \beta_j \sum_{i=1}^N e_{ij} x_i = \sum_{j=1}^J \beta_j w_j = 0, \quad (3)$$

$$\sum_{k=1}^K \gamma_k \sum_{i=1}^N e_{ik} x_i = \sum_{k=1}^K \gamma_k v_k = 0. \quad (4)$$

Here N is the total number of firms in a given period. Equation (2) can then be estimated subject to the restrictions (3) and (4). As in several of the studies referred to above, we estimate (2) using weighted least squares. In doing so, each stock return is weighted by its beginning-of-period share x_i of the global stock market capitalization (computed as a sum of the market capitalization of all the N firms comprising the cross-section), so that w_j corresponds to the market capitalization of industry j as a share of the global market, while v_k is the market capitalization of country k as a share of the global market.

The weighted least squares estimates of the parameters in (2) subject to (3) and (4) yields orthogonal excess return vectors for the various J industries and K countries for every t . An advantage of constructing country and industry portfolios this way is that the number of firms at each cross-section can vary and yet a balanced panel of portfolios of country and industry specific excess returns can be formed, effectively summarizing the relevant information from the original unbalanced panel.

Defining excess return vectors as

$$\beta_t = \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \\ \vdots \\ \beta_{Jt} \end{pmatrix}, \quad \gamma_t = \begin{pmatrix} \gamma_{1t} \\ \gamma_{2t} \\ \vdots \\ \gamma_{Kt} \end{pmatrix},$$

we can re-write equation (2) as:

$$R_{ijkt} = \alpha_i + \mathbf{e}'_{i\beta} \boldsymbol{\beta}_t + \mathbf{e}'_{i\gamma} \boldsymbol{\gamma}_t + \varepsilon_{it}. \quad (5)$$

where $\mathbf{e}_{i\beta}$ is a $J \times 1$ vector of zeros with a one in the i th firm's industry, while $\mathbf{e}_{i\gamma}$ is an $K \times 1$ vector of zeros with a one in the i th firm's country.

A. Country- and Industry-Specific Return Dynamics

While the earlier literature has not attempted to link the individual industry (β_t) and country components (γ_t) over time, we will allow for such dependencies in these components in a flexible manner which does not impose linearity or serial independence *a priori*. In particular, we follow the large empirical literature that has documented the presence of persistent 'regimes' in a variety of financial time series. Ang and Bekaert (2002), Driffill and Sola (1994), Gray (1996), Hamilton (1988)) find evidence of multiple states in the dynamics of interest rates, while Ang and Bekaert (2001), David and Veronesi (2001), Guidolin and Timmermann (2002), Perez-Quiros and Timmermann (2000), Turner, Starz and Nelson (1989) and Whitelaw (2001) provide evidence for stock market returns. Typically these states capture periods of high and low volatility in returns. Most of these papers model states in univariate return series or in pairs of returns (e.g., Ang and Bekaert (2001), Perez-Quiros and Timmermann (2000)).³

Specifically, we assume that there are separate "state" variables driving returns on the global, industry, and country portfolios labeled $s_{\alpha t}, s_{\beta jt}, s_{\gamma kt}$. We show in the empirical section that the data justifies this assumption. If, furthermore, these state processes are industry and country specific, we can write returns on the global, industry and country portfolios as follows:

$$\begin{aligned} \alpha_t &= \mu_{\alpha s_{\alpha t}} + \sigma_{\alpha s_{\alpha t}} \varepsilon_{\alpha t}, \\ \beta_{jt} &= \mu_{\beta j s_{\beta jt}} + \sigma_{\beta j s_{\beta jt}} \varepsilon_{\beta jt}, \\ \gamma_{kt} &= \mu_{\gamma k s_{\gamma kt}} + \sigma_{\gamma k s_{\gamma kt}} \varepsilon_{\gamma kt}. \end{aligned} \quad (6)$$

Suppose, for example, that there are two states for the global return process so $s_{\alpha t} = 1$ or $s_{\alpha t} = 2$. Then the mean return on the global return component in any given period, t , is either $\mu_{\alpha 1}$ or $\mu_{\alpha 2}$, while its volatility is either $\sigma_{\alpha 1}$ or $\sigma_{\alpha 2}$. Similarly, if the j th industry state variable can take two values, $s_{\beta jt} = 1$ or $s_{\beta jt} = 2$, then the j th industry's mean return at time t is either $\mu_{\beta j 1}$ or $\mu_{\beta j 2}$ while its volatility is either $\sigma_{\beta j 1}$ or $\sigma_{\beta j 2}$.

³ Guidolin and Timmermann (2002) also consider a model for the joint dynamics of returns on small firms, large firms, bonds and T-bills.

One could of course impose a constraint that the mean return was the same in the two states in which case our model would simply capture time-varying volatility. However, on theoretical grounds we would expect the mean returns to be different in the high and low volatility state, so we allow the mean parameters to be state-dependent.

How the state processes alternate between states is obviously important. We follow conventional practice and assume constant state transition probabilities for the global return process as well as for the individual country and industry return processes:⁴

$$\begin{aligned} \Pr(S_{\alpha t} = s_{\alpha} | S_{\alpha t-1} = s_{\alpha}) &= p_{\alpha s_{\alpha} s_{\alpha}}, \\ \Pr(S_{\beta jt} = s_{\beta_j} | S_{\beta jt-1} = s_{\beta_j}) &= p_{\beta_j s_{\beta_j} s_{\beta_j}}, \\ \Pr(S_{\gamma kt} = s_{\gamma_k} | S_{\gamma kt-1} = s_{\gamma_k}) &= p_{\gamma_k s_{\gamma_k} s_{\gamma_k}}. \end{aligned} \quad (7)$$

Here $p_{\alpha 11}$ is the probability that the global return process remains in state 1 if it is already in this state, $p_{\beta_j 11}$ is the probability that the j th industry state variable remains in state 1 and so forth. This means that the regimes are generated by a discrete state homogenous Markov chain. We will be interested in studying the state probabilities implied by our models given the current information set, Γ_t , which comprises all information up to time t , i.e., $\pi_{s_{\alpha t}} = \Pr(S_{\alpha t} = s_{\alpha} | \Gamma_t)$, $\pi_{s_{\beta_j t}} = \Pr(S_{\beta_j t} = s_{\beta_j} | \Gamma_t)$, $\pi_{s_{\gamma_k t}} = \Pr(S_{\gamma_k t} = s_{\gamma_k} | \Gamma_t)$, where Γ_t is the current information set containing (at a minimum) returns up to time t . As we shall see in the empirical section, the time series of these probabilities, extracted from the data, provide information about high and low volatility states.

Finally, we assume that the innovation terms, $\varepsilon_{\alpha t}$, $\varepsilon_{\beta jt}$ and $\varepsilon_{\gamma kt}$ are normally distributed. Notice that this means that the return process will be a mixture of normal random variables. This is a distribution that is capable of accommodating features such as skews and fat tails that are frequently found in financial return distributions.

Under this model, the return on the i th company in industry j and country k is given by

$$R_{ijkt} = \mu_{\alpha s_{\alpha}} + \mu_{\beta_j s_{\beta_j}} + \mu_{\gamma_k s_{\gamma_k}} + \sigma_{\alpha s_{\alpha}} \varepsilon_{\alpha t} + \sigma_{\beta_j s_{\beta_j}} \varepsilon_{\beta jt} + \sigma_{\gamma_k s_{\gamma_k}} \varepsilon_{\gamma kt} + \varepsilon_{it}. \quad (8)$$

⁴ While it is possible to further extend the model by allowing for time-varying state transition probabilities, c.f., Gray (1996), we do not consider this complication of our model here. We keep the model relatively simple to facilitate generalization of the model to the case with multiple industries or countries, where the number of parameters already is rather large.

Clearly each stock will be affected by separate global, industry and country regimes plus an idiosyncratic error term so the model provides a flexible characterization of returns on individual stocks.

B. Common Nonlinear Components

The above model assumes that the state processes or “regimes” underlying returns on the industry and country portfolios are different for different countries and industries. This represents a natural starting point insofar as many factors underlying these portfolios’ risk and return characteristics could well be country- and industry specific.

However, it is possible that the state variable driving the industry and country returns shares an important common component across industries and country returns. This could be induced, for example, by an oil shock to the extent that the latter tends to have a large differential effect across industries and a far more homogenous effect across countries. Similarly, there may be common institutional shocks that spread along country lines as opposed to industry lines. One example is the growing worldwide consensus to keep inflation at bay and the associated institutional changes in central bank mandates—a factor which has been deemed to help explain the decline of world inflation and the concomitant upward trend in global asset prices since the mid-1980s (IMF, 2000).

If such dependencies exist across countries or across industries, a more efficient way to gain information about the underlying state variable is to estimate a multivariate regime-switching model jointly for several portfolios. To account for the possibility that a common state factor is driving the individual industry returns on the one hand and the individual country returns on the other hand, we consider the following model:

$$\begin{aligned}\alpha_t &= \mu_{\alpha s_{\alpha t}} + \varepsilon_{\alpha s_{\alpha t}}, \\ \beta_t &= \mu_{\beta s_{\beta t}} + \varepsilon_{\beta s_{\beta t}}, \\ \gamma_t &= \mu_{\gamma s_{\gamma t}} + \varepsilon_{\gamma s_{\gamma t}},\end{aligned}\tag{9}$$

where $\mu_{\alpha s_{\alpha t}}$ is the scalar global mean return in state $s_{\alpha t}$, $\mu_{\beta s_{\beta t}}$ is a J -vector of industry means in state $s_{\beta t}$, $\mu_{\gamma s_{\gamma t}}$ is a K -vector of country means in state $s_{\gamma t}$. Furthermore, the innovations to returns have zero mean with state-specific variances $\varepsilon_{\alpha s_{\alpha t}} \sim (0, \sigma_{\alpha s_{\alpha t}}^2)$, $\varepsilon_{\beta s_{\beta t}} \sim (0, \Omega_{\beta s_{\beta t}})$, $\varepsilon_{\gamma s_{\gamma t}} \sim (0, \Omega_{\gamma s_{\gamma t}})$, where $\sigma_{\alpha s_{\alpha t}}^2$ is the scalar variance of global return in state $s_{\alpha t}$, $\Omega_{\beta s_{\beta t}}$ is the $J \times J$ variance-covariance matrix of industry returns in state $s_{\beta t}$, $\Omega_{\gamma s_{\gamma t}}$ is the $K \times K$ variance-covariance matrix of country returns in state $s_{\gamma t}$.

State transitions for this common factor case are still assumed to be time-invariant:

$$\begin{aligned}
 \Pr(S_{\alpha} = s_{\alpha} | S_{\alpha-1} = s_{\alpha}) &= p_{\alpha s_{\alpha} s_{\alpha}}, \\
 \Pr(S_{\beta} = s_{\beta} | S_{\beta-1} = s_{\beta}) &= p_{\beta s_{\beta} s_{\beta}}, \\
 \Pr(S_{\gamma} = s_{\gamma} | S_{\gamma-1} = s_{\gamma}) &= p_{\gamma s_{\gamma} s_{\gamma}}.
 \end{aligned}
 \tag{10}$$

The regime switching model is fully specified by the state transitions (10), the functional form of the return equation (9) and the assumed “mixture of normals” density. However, estimation of the model is complicated by the fact that the state variable is unobserved or latent. We deal with this by obtaining maximum likelihood estimates based on the EM algorithm.

A major advantage of our common nonlinear factor approach is that it allows us to extract volatility estimates of portfolio strategies involving an arbitrary number of countries or industries in addition to the global component. As explained by Solnik and Roulet (2000), the standard way to capture time-variation in market volatility and correlations is by using a fixed-length rolling window of, say, 36 or 60 months of returns data and estimate cross-correlations for pairs of countries (c.f. Solnik, Boucelle and Le Fur, 1996). This approach has three major disadvantages compared to our approach. First, since the rolling window does not rely on the full data sample, it is likely to lead to imprecise estimates of volatilities and correlations which typically require relative large data samples for precise estimation. Second, by construction as they present moving averages of volatilities, rolling window estimates cannot capture relatively short-lived volatility bursts that may be economically interesting and important to investors’ risk management. Third, rolling window estimates provide unconditional estimates of volatilities and correlations and do not exploit any dynamic structures in the covariance of portfolio returns.

In contrast, notice the richness of the dynamics in our model: for a given state the mean and variance of returns are constant, as are the correlations between various industry (country) portfolios. However, as the state probabilities vary over time, the conditional correlation, mean and variances of returns are allowed to fluctuate. Using the ex-ante state probabilities, the model allows for time-varying expected returns and measures of risk. The mechanism for generating such time-variations arises because of the time-varying state probabilities. The general model also captures the correlations between returns on different country and industry portfolios.

It is of course possible to construct an even more restrictive version of (9) that assumes the global, industry and country factors are driven by the same state process. However, as we shall see in the empirical section, the data does not support such a specification. This is, perhaps, unsurprising since the sources of discrete changes (economic policy, technology shocks etc) are likely to be quite different at these levels.

III. DATA

The data cover monthly total returns and market capitalizations for up to 3,951 firms in developed stock markets over the period February 1973 to February 2002.⁵ Country coverage spans Australia, Belgium, Canada, Denmark, France, Germany, Ireland, Italy, Japan, Netherlands, Switzerland, the United Kingdom and the United States. While data are available for other national stock markets, estimation of the econometric model for a significantly larger number of countries becomes unfeasible and probably redundant in any case, since the group of countries considered is sufficiently representative of the global stock market (see below). Firms in these 13 countries are grouped into one of 11 FTSE industry sectors: resources, basic industries, general industries, cyclical consumer goods, non-cyclical consumer goods, cyclical services, non-cyclical services, utilities, information technology, financials and others.⁶ While some recent papers argue in favor of a finer industry

⁵ Monthly total returns are computed in local currency using data from Datastream/Primark. The return calculation assumes immediate reinvestment of dividends. These local currency returns are converted to U.S. dollars using end-of-month spot exchange rates. The beginning-of-month stock market capitalizations are converted into U.S. dollars using the beginning-of-month dollar price of one unit of local currency. Expressing all returns and market cap data in US dollars implicitly reflects the perspective of a currency unhedged equity investor whose objective is to maximize U.S. dollar returns. It is important to note, however, that since changes in equity returns far overwhelm those associated with currency fluctuations, expressing returns and market caps in the distinct national currencies should not change the thrust of the results, as previous studies have found (Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998; Brooks and Catão, 2000). Developing countries were excluded from the sample altogether because none of these countries had data stretching back to the early 1970s, so that their inclusion would probably distort the representativeness of the sample over time and, in any case, entail too short time series for the estimation of Markov-switching processes for the respective country portfolios.

⁶ These broad FTSE classification can be further broken down as follows: Resource industries comprise mining, oil and gas; basic industries comprise chemicals, construction and building materials, forestry and paper, and steel and other metals; general industries encompass aerospace & defense, diversified industrials, electronic & electrical equipment, engineering & machinery; cyclical consumer goods comprise automobiles, household goods & textiles; non-cyclical consumer goods include beverages, food producers & processors, health, packaging, personal care & household products, pharmaceuticals, and tobacco; cyclical services comprise distributors, general retailers, leisure, entertainment & hotels, media & photography, restaurants, pubs & breweries, support services, and transport; non-cyclical services comprise food & drug retailers, and telecommunication services; utilities comprise electricity, gas distribution, and water; financials comprise banks, insurance companies, investment companies, real estate firms and specialty & other finance;

(continued)

disaggregation, the level of disaggregation used here is sufficient not only because it follows the traditional industry breakdown used by portfolio managers and much of the academic literature, but also because it clearly distinguishes new industries which appear to have distinct time series dynamics of stock returns (such as information technology—see Brooks and Catão, 2000) from “old economy” industries.⁷

A desirable feature of this data is that it be a realistic and unbiased representation of the global stock market. As of December 1999, the total capitalization of the sample comes to \$26.3 trillion or 80 percent of stock market capitalization in advanced countries as measured by the IFC yearbook and 73 percent of the world market capitalization (i.e. including developing countries). Coverage deteriorates somewhat towards the beginning of the sample but because the data comprises the largest and internationally most actively traded firms in key markets such as the United States, Japan, and the United Kingdom throughout, the sample can be deemed as quite representative from the viewpoint of the global investor. It should be noted, however, that the deterioration in coverage reflects two deficiencies of the data set. First, it is subject to survivorship bias, meaning that only firms surviving over the full sample period are covered. No doubt this bias is important, especially in the context of global shocks such as that of the 1987 crash and the virulent recession of the early 1990s in Europe and Japan. But this problem is partly offset by the fact that the data omit a large number of small firms which typically face greater bankruptcy risks and whose influence in a market capitalization weighted world portfolio is low in any case. A potentially more serious flaw of the data is that it includes only post-merger companies, dropping companies that go into the merger. It is possible that this may bias the estimates in favor of finding more pronounced global industry effects in more recent years in the sample.

On the positive side, our sample stretches over a much longer time period than those in the studies referred to in the introduction, and this is a crucial advantage required for estimation of regime switching processes with some degree of precision. As we shall see, most regimes tend to be quite persistent so identifying them requires a time series as long as that considered in our study. No single country is represented by less than 28 firms on average (Ireland and Denmark) and, in the case of large economies such as the US and Japan, coverage approaches 1,000 firms towards the end of the sample from a minimum of 377 firms at the beginning of the sample (February 1973). This reasonably large time series and cross-sectional dimension of the data probably eliminates any significant distortion in the

information technology comprises information technology hardware and software & computer services; other industries include non-classified miscellaneous.

⁷ While Griffin and Karolyi (1998) note that a finer industry disaggregation may yield a more accurate measure of industry effects, their main result – the dominance of country-specific effects—hardly changes with the move to a finer industry breakdown (they have nine broad industry categories and 66 more disaggregated industries). Meanwhile, Heston and Rouwenhorst’s (1995) results are based on seven broad industry categories.

econometric results arising from the deficiencies mentioned above. Moreover, to the extent that much of our analysis focuses on the variance of stock returns rather than on their mean values, the main results are unlikely to be vulnerable to the traditional survivorship bias problem.

IV. EMPIRICAL RESULTS

This section first presents the full-sample results for the returns on the individual industry- and country portfolios considered in our analysis. These results serve as a benchmark for the subsequent dynamic analysis and also allow us to relate our findings to the extant literature. Next we model nonlinear dynamics in the individual country—and industry portfolios. Finally we consider the presence of common dynamic components in the country and industry returns.

Table 1 presents some summary statistics for the distribution of the country—industry and world portfolios. All country and industry portfolio returns are measured in excess of the world portfolio so the mean returns on these portfolios are close to zero on average.⁸ The standard deviations average 4.89 percent per month for the country portfolios and 2.96 percent for the industry portfolios, thus verifying the finding in the literature that, on average, country factors matter more than industries for explaining variations in stock returns. Country portfolios tend to be slightly more strongly positively skewed than the industry portfolios while, interestingly, returns on the global portfolio are not skewed. There is also strong evidence of excess kurtosis in most of the portfolios. Accordingly, Jarque-Bera test statistic for normality rejected the null of normally distributed returns for all portfolios except for Switzerland and Japan.⁹ This is of course the type of situation where mixtures of normals may be better able to capture the underlying return distribution.

A. Nonlinear Dynamics in Returns

Previous studies of country—and industry effect in international stock returns have been based on the assumption of a single state, so it is important to investigate the validity of this assumption. To determine whether a regime switching model is appropriate for our analysis, we first verify that two or more states characterize the return generating process of the individual industry and country portfolios. For this purpose we report the outcome of the statistical test proposed by Davies (1977). Standard likelihood ratio tests do not account for the problem associated with unidentified nuisance parameters under the null hypothesis of a single regime. The Davies test takes this problem into account. The results are shown in Table 2. For 10 out of 13 countries and 10 of 11 industries, the null of a single state is

⁸ The only reason the averages are not exactly equal to zero is that we are reporting arithmetic averages whereas the world portfolio is based on capitalization-weighted returns.

⁹ Results of the Jarque-Bera test statistics are available from the authors upon request.

rejected at the 1 percent critical level. Linearity is also strongly rejected for the global portfolio. Hence there is overwhelming evidence of nonlinear dynamics in the form of multiple regimes in country, industry and global returns.

These test results suggest that there are at least two regimes in the vast majority of return series. However they do not tell us if two, three or even more states are needed to model the return dynamics. To choose among model specifications with multiple states, Table 3 reports the results of three standard information criteria that are designed to trade off fit (which automatically grows with the number of parameters and thus with the number of underlying states) against parsimony (as measured by the total number of parameters). We report results using the Akaike (AIC), the Schwarz Bayesian (BIC) and the Hannan-Quinn (HQ) information criteria. For the 13 country portfolios, the three criteria unanimously point to a single state for Canada and Switzerland and three states for the UK, and at least two of the above criteria suggest that stock returns in all other countries are better modeled as a two-state process.¹⁰

Turning to the industry portfolios, the results are even more homogenous, with the BIC and HQ criteria selecting a two-state model for 9 industries out of 11. At the same time, all three criteria indicate that stock returns in Resources are best captured through a three-state model. Only for cyclical services is there considerable difference—the BIC and HQ choosing a single-state model while the AIC selects a three-state specification. Finally, regarding the global portfolio, AIC and HQ choose a two-state specification, while the BIC marginally selects a single-state specification. Overall, therefore, the results in Table 3 strongly indicate the presence of two states in the dynamics of the various portfolio returns. Accordingly, the subsequent analysis is based on this specification.

B. Country Return Dynamics

Panel A of Table 4 shows the maximum likelihood estimates of the parameters of the two-state regime-switching model fitted to returns on the individual country portfolios for which there was evidence of multiple states, i.e. all countries except for Canada and Switzerland. The ordering of states is, of course, arbitrary so we stick to the convention of listing the state with the highest volatility as state 1, while state 2 is the state with the lowest volatility. Using this convention, the first two columns in Table 4 show the volatility (standard deviation) estimates for the two states, while columns 3 and 4 provide the estimated state transition probabilities p_{11} (the probability of staying in state 1) and p_{22} (the probability of staying in state 2) followed by the steady state probabilities (columns 5 and 6) and the average monthly duration of the two states (columns 7 and 8).

¹⁰ The finding of a single state for Canada and Switzerland is consistent with the Davies' tests in Table 2 which could not reject linearity for these two countries.

Differences between the volatility parameters of the two regimes are highly significant, both economically and statistically.¹¹ The average country volatility estimate is 7.1 percent per month in the high volatility state, almost twice the value in the low volatility state (3.6 percent per month). In all but one country, Japan, the high volatility state has the lowest persistence. This is consistent with the notion that bursts of volatility do not last all that long. In some countries the duration of the high volatility state is very short. For example, for Belgium the high volatility state lasts less than three months on average, while the low volatility state has an average duration of more than 25 months. Countries that have volatility bursts of very short duration may generate mean returns that appear rather extreme in the high volatility state, in part because volatility is so high in this state and in part because the mean return estimate is based on relatively few observations. Fortunately the vast majority of countries have 'stayer probabilities' for the low volatility state that are well above 90 percent. On average, across countries, the duration of the high volatility state is 16 months while it is 39 months for the low volatility state. As a consequence, as shown by the steady-state probabilities, an average of 70 percent of the time is spent in the low volatility state while 30 percent of the time is spent in the high volatility state.

To assist in the economic interpretation of the two regimes, Figure 1 plots for each country the smoothed probability of the high volatility state (state 1). The time-series properties are quite mixed, reflecting the well-known heterogeneity of country factors documented in the literature (more on this below). Nevertheless, clearly defined persistent states emerge in all countries but Japan and the Netherlands. Also noticeable in Figure 1 is a clear tendency towards a switch to the low volatility state in the last part of the sample for the US, the UK, France, Germany, Australia and Denmark. As discussed further below, this lends credibility to the notion that the contribution from the country component to explaining stock return variations has recently declined in significance. Moreover, the results indicate that this decline occurred some time during the nineties, albeit not necessarily at the same time in all countries.

C. Industry Return Dynamics

As with the country portfolios, Table 4 shows that the difference between the volatility levels in the two states for the industry portfolios is also very large, with average industry volatility of 4.3 percent per month in the high volatility state and average volatility of 2.1 percent in the low volatility state. Despite this similarity, the dynamics of the low and high volatility regimes is quite different for the industry portfolios than for the country

¹¹ Although we are not primarily concerned with the mean return variation across states, the mean return computed across countries is estimated at 0.73 percent per month in the high volatility state and -0.26 percent in the low volatility state. One should not put too much into the mean estimates in the two states, however, since they are associated with considerable uncertainty, particularly for countries such as Belgium, Italy and Ireland where little time is spent in the high volatility state.

portfolios. In all industries except for Resources, the ‘stayer’ probability is higher in the low volatility state than in the high volatility state. For the industry portfolios both states are highly persistent with average stayer probabilities of 91 percent in the low volatility state and 94 percent in the high volatility state. The high volatility state is thus clearly more persistent for the industry portfolios than for the country portfolios. Consequently on average 39 percent of the time is spent in the high volatility state in the case of the industry portfolios. Again, the average duration of the low volatility state is more than twice as long as that of the high volatility state.

To assist with the economic interpretation of these results Figure 2 presents the smoothed probabilities of the high volatility state for the industries where multiple states were identified. The high volatility regimes of the industry portfolio returns are clearly more homogenous than the regimes identified for the country returns in Figure 1—a result consistent with the findings of Heston and Rouwenhorst (1994) who also report that industry volatility is more uniform than country volatility. This similarity is all the more remarkable in the present context since each of the plots is based on univariate regressions and thus does not utilize information about returns in other industries. In most industries, the states persist for long periods of time and are very clearly separated by the data in the sense that the probability of the regime from which the returns data in a given month is drawn is almost always far from 0.5. In most industries the high volatility state emerged in 1986 and again from 1998 and onwards. There is also a tendency for common high volatility around 1974–75.

D. A Joint Model of Common Components

The extant literature seeks to answer how much country and industry effects matter “on average”. The empirical results thus far have identified regimes that are specific to each industry or country portfolio. However, addressing the question of the overall importance of industry and country effects, requires studying common country and common industry effects. To do so, we next study a model in which there are separate regimes in the joint country and in the joint industry portfolio returns. This yields a nonlinear dynamic common factor model.¹²

We do so by estimating joint regime switching models for the return series on the 13 country portfolios and 11 industry portfolios. To our knowledge, regime switching models on such large systems of variables have not previously been estimated jointly. The joint

¹² The vast majority of recent work on dynamic common factor models assumes a linear factor structure, c.f. Stock and Watson (1998). We allow for nonlinear dynamics principally because of our interest in extracting common factors in the volatility of returns on various portfolios and also because of the strong empirical evidence of time-varying volatilities in stock returns.

estimation of the parameters of a highly nonlinear model for such a large system is a nontrivial exercise.

Table 5 presents estimates of the transition probabilities and average state durations and the outcome of the Davies test for multiple states. Estimation results are shown in Table 6 which also presents results for the global portfolio. Since the joint country model has 210 parameters while the joint industry model has 156 parameters (most of which measures the covariance between industry returns in the two states), we do not report all the estimates and instead concentrate on the standard deviations.

Again, the null hypothesis of a linear model with a single state is strongly rejected for the country, industry, and world models. The Davies test yields p-values below 0.001 for all models. All three information criteria supported a two-state model over the single-state model in the case of the joint industry and joint country models, while both the AIC and the HQ criterion supported the two-state specification over the one-state model for the global return model.

First consider the common country component. Table 5 shows that the two states identified in country returns have persistence parameters of 0.975 and 0.976. With such high persistence parameters, the durations of the two states are very high at 40 and 42 months, respectively. Clearly this model is picking up long-lasting regimes in the common component of the country portfolios. The average volatility is around 4.9 percent in both states, so the states are no longer defined along high and low volatility, at least not on average. Even so, the volatility is markedly higher in the first state for the US. Average correlations across country portfolios are close to 0.1 in both states, although, again, for some countries there are some interesting differences. For example, the US has a small positive average correlation of 0.05 with other countries in state 1 (the high volatility state) and a large negative correlation (-0.33) with other countries in the low volatility state.¹³ The implication of this is that the diversification possibilities for a US investor are reduced in the high volatility state, a finding consistent with much of the existing literature, c.f. Longin and Solnik (2001).

Very different results emerge from the parameter estimates for the joint industry model. In the low volatility state (state 2) the average volatility is 2.27 percent while it is more than twice as high in the high volatility state (4.67). Average correlations are now negative in the low volatility state and zero in the high volatility state. State transition probabilities for the industry returns listed in Table 5 at 0.87 and 0.96 are quite high and imply average duration of 27 months in regime 1 and 26 months in regime 2. Consequently the steady state probabilities are 23 and 77 percent, so that three times as much time is spent by the industry portfolios in the low volatility regime (state 2).

¹³ While these numbers may seem low, it should be recalled that this is only because the global return factor (common to all stocks) has been taken out.

While the extent to which industry return correlations vary across states is not uniform, it is interesting to note that the correlation between information technology (IT) returns and the other industry returns is large and negative (-0.28) in the high volatility state. Since the smoothed state probability plots suggest that the common industry component has been in the high volatility state since 1998, it is clear that, during the recent IT boom and bust, the correlation between the IT and other industry returns was lower than during its low volatility state, where the correlation was -0.10 on average.

Figure 3 plots the time series of the smoothed probabilities for the high volatility state identified by the common country and common industry models as well as the model for global returns. The high persistence in the common country component stands out. For example, the common country effect stays in the same regime over the period 1986–1997, although it is difficult to interpret in terms of periods of high and low volatility.¹⁴ In contrast, the global return component follows shorter, cyclical movements that nevertheless are well separated by the model. This model thus identifies more regime shifts than the models fitted to the common country and industry portfolios. The common industry regime identifies four high volatility periods around the oil shock of the early seventies (1974), an episode in 1980–81, a spell from 1986 to September 1987 followed by the more recent period beginning in early 1998.

Although the series are clearly different, they still share some similarities. For a significant part of the period, the state probability for the common country factor is negatively correlated with that for the common industry factor, pointing to the alternating importance of these two factors in explaining overall stock return volatility over time. (The correlation between the smoothed state probabilities of the common industry and country return components is -0.27). The common country state variable has a correlation of -0.10 with the global state variable. Finally the industry and global state processes are strongly positively correlated with a sample correlation of 0.42 . This is to be expected, since many shocks to the global component are industry specific shocks, such as the oil shocks of the 1970s and the worldwide IT boom in recent years. We return to this point below.

These results appeal to intuition. The finding that the global return component is the least persistent factor makes sense as it is likely to capture a variety of large, common economic shocks typically associated with the global business cycle. In contrast, common country components are likely to undergo less frequent shifts as they tend to be more based on structural relations that are more slowly evolving, especially in countries with relatively stable institutions such as the advanced countries comprising our dataset. The common industry component lies somewhere in between in terms of its persistence.

¹⁴ Interestingly, comparing the state plots in Figure 1 to the middle panel in Figure 3, the single country whose state probability series is most closely correlated with the common country state variable (at a correlation of 0.62) is the United States.

V. VARIANCE DECOMPOSITIONS

A key question addressed by the literature on country and industry effects is the relative size of these effects as measured by the relative volatility of geographically or industrially diversified portfolios. To get a first measure of how the total systematic variance evolves over time, we simply sum the global variance, the average country variance and the average industry variance (all based on conditional moment information reflecting the time-varying state probabilities) as follows:

$$\begin{aligned} \sigma_t^2 = & \sum_{s_{ca}} \pi_{s_{ca}} (\sigma_{s_{ca}}^2 + (\mu_{\alpha s_{ca}} - \bar{\mu}_{ca})^2) \\ & + \sum_{s_{\beta t}} \pi_{s_{\beta t}} (\omega'_{\beta t} \Omega_{\beta s_{\beta t}} \omega_{\beta t} + \omega'_{\beta t} (\mu_{\beta s_{\beta t}} - \bar{\mu}_{\beta t})^2) \\ & + \sum_{s_{\gamma t}} \pi_{s_{\gamma t}} (\omega'_{\gamma t} \Omega_{\gamma s_{\gamma t}} \omega_{\gamma t} + \omega'_{\gamma t} (\mu_{\gamma s_{\gamma t}} - \bar{\mu}_{\gamma t})^2), \end{aligned} \quad (11)$$

where $\omega_{\beta t}$ is the vector of weights for the industry portfolios and $\omega_{\gamma t}$ is the vector of weights of country portfolios. $\bar{\mu}_{ca} = \sum_{s_{ca}} \pi_{s_{ca}} \mu_{\alpha s_{ca}}$ is the conditional expectations of the global portfolio returns, $\bar{\mu}_{\beta t} = \sum_{s_{\beta t}} \pi_{s_{\beta t}} \mu_{\beta s_{\beta t}}$ and $\bar{\mu}_{\gamma t} = \sum_{s_{\gamma t}} \pi_{s_{\gamma t}} \mu_{\gamma s_{\gamma t}}$ are $J \times 1$ and $K \times 1$ vectors of conditionally expected returns on the industry and country portfolios, respectively. The first component in (11) accounts for the total variance of the global return component. The second component is the value-weighted industry variance, while the third component is the value-weighted country variance. Besides accounting for state-dependent covariances, there is an extra component in each of these terms arising from variations in the means across states. Notice that this measure of total systematic variance changes over time due to time-variations in the state probabilities.¹⁵

Figure 4 plots the time-series of the systematic volatility component computed by taking the square root of (11). Systematic volatility varies considerably over time from a low point around 2.8 percent to a peak around 5.5 percent per month. It was very high around 1974/75, 1980, 1987, 1991, and from late 1997 onward. At these times, the systematic volatility component was close to twice as large as during the low volatility regimes that occurred in the late seventies and mid-nineties. Recalling that the volatility of the country component does not vary much across the two states, while conversely the volatility of the industry and global portfolio returns are about twice as high in the high volatility state as they

¹⁵ The squared terms in the variance expression enter due to the binomial nature of the state variable, c.f. Timmermann (2000).

are in the low volatility state, it is easy to understand the figure. Systematic volatility tends to be high when the common industry component and the global component are both in the high volatility state at the same time, i.e. in 1974, 1980, 1987 and from 1998 to 2002. Conversely, if they are simultaneously in the low volatility state, then systematic volatility will be low. Overall, our estimates also indicate that systematic volatility is trendless, a result consistent with Schwert's (1989) finding that market volatility has no significant long-term trend.

The measure of systematic variance in (11) readily lends itself to a decomposition of the total systematic variance into its three constituents. Figure 5 shows the fraction of total systematic variance represented by the average country, average industry and global components scaled by the sum of these. Time variation in the (average) country fraction is very large and ranges from about two-thirds to one-third as in recent years. In particular, the importance of the country factor has been noticeable lower in periods of well-known global shocks such as the 1974-75 oil shock, the 1987 stock market crash and the information technology boom of the late 1990's. Such ups and downs in the relative contribution of the country factor do not lend much support to the notion sometimes popularized in the financial press that greater cross-border freedom in capital movements over the past decade or so has been gradually undermining the importance of country-specific shocks (see, e.g., Farrell, 2000), as changes in the country factor contribution have been anything but monotonic.

Likewise, the fraction of the total systematic volatility due to the industry component also varies considerably as shown in the middle panel of Figure 5. It rises to about thirty percent in the immediate aftermath of the two oil shocks of the 1970s (1974 and 1980/81), during the stock market crash of 1987, and during the IT boom and bust cycle from 1997/98 onwards. In the context of the existing literature, the estimated average level in the 10 to 15 percent range is slightly higher than the 7 percent figure of Heston and Rouwenhorst (1995) and more than twice as high as the estimates in Griffin and Karolyi's (1998)—both based on linear single-state models as discussed above.¹⁶ Figure 5 clearly unveils significant changes in the relative importance of the industry factor and shows that its recent rise has in fact been the most persistent of all over the past thirty years, though not quite yet to the point where its relative contribution to systemic volatility has surpassed that of the country factor as claimed by Cavaglia et al. (2000). As shown in the bottom panel of Figure 5, this is

¹⁶ Griffin and Karolyi (1998) present two sets of estimates, one using a nine-sector breakdown and the other using 66 industry breakdown. They find that the mean industry factor contribution to total return variance are 2 and 4 percent respectively, a lot lower therefore than the above estimates. One possible reason for the lower estimate of Griffin and Karolyi (1998) relative to Heston and Rouwenhorst (1995) as well as ours is the inclusion of emerging markets in their sample. As country-specific shocks have been shown to play a greater role in the determination of stock returns in emerging markets (Serra, 2000), this is to be expected. However, we show below that much of the difference appears to be model and time dependent. Furthermore, Griffin and Karolyi consider a much shorter sample of weekly returns so differences in estimates are not all that surprising.

partly due to the concomitant rise of the global factor contribution to overall stock return volatility in recent years which has filled some of the gap arising from the decline in country-specific volatility.

An alternative and complementary measure of the relative significance of the industry and country contributions to portfolio returns follows the decomposition scheme proposed in Griffin and Karolyi (1998) and replicated by others (e.g., Baca et al., 2000). The methodology proposed in this paper allows us to extend this framework by both letting the relative contributions of each factor vary across states and taking into account the various industry covariances within each state. As in Griffin and Karolyi (1998), let the excess return on the national stock market or portfolio of country k (over and above the global portfolio return $\hat{\alpha}$) be decomposed into country k 's unique industry weights times the industry returns summed across industries (i.e., $\sum_{j=1}^J \omega_{jka}^\beta \hat{\beta}_{jt}$) plus a "pure" country effect $\hat{\gamma}_k$:¹⁷

$$R_{kt} - \hat{\alpha}_t = \sum_{j=1}^J \omega_{jka}^\beta \hat{\beta}_{jt} + \hat{\gamma}_k, \quad (12)$$

where ω_{jka}^β is the j th industry's weight in country k . The variance of this excess return conditional on the country state being $s_{\gamma t}$ and the industry state being $s_{\beta t}$ is

$$\text{Var}(R_{kt} - \hat{\alpha}_t | s_{\beta t}, s_{\gamma t}) = (\omega_{ka}^\beta)' \Omega_{\beta s \beta} \omega_{ka}^\beta + \mathbf{e}_k' \Omega_{\gamma s \gamma} \mathbf{e}_k + 2(\omega_{ka}^\beta)' \text{Cov}(\beta_{jt}, \gamma_{kt} | s_{\beta t}, s_{\gamma t}), \quad (13)$$

where ω_{ka}^β is the J -vector of market capitalization weights of the industries in country k .

Similarly, the excess return on the portfolio of industry j (over and above the global portfolio) can be decomposed into industry j 's unique country weights times the country returns summed across countries plus a pure industry effect, $\hat{\beta}_{jt}$:

$$R_{jt} - \hat{\alpha}_t = \sum_{k=1}^K \omega_{jka}^\gamma \hat{\gamma}_{kt} + \hat{\beta}_{jt}, \quad (14)$$

¹⁷ It is straightforward to show that this decomposition follows from re-writing equation (2) for each individual country portfolio, where the individual firm's weight is the share of that firm in total market capitalization of the respective country portfolio.

where ω_{jk}^y is the k th country's weight in industry j . The variance of this excess return conditional on the country state being $s_{\gamma t}$ and the industry state being $s_{\beta t}$ is

$$\text{Var}(R_{jt} - \hat{\alpha}_t | s_{\beta t}, s_{\gamma t}) = (\omega_{jt}^y)' \Omega_{\gamma s_{\gamma}} \omega_{jt}^y + \mathbf{e}_j' \Omega_{\beta s_{\beta}} \mathbf{e}_j (\omega_{jt}^y)' + 2\text{Cov}(\beta_{jt}, \gamma_{kt} | s_{\beta t}, s_{\gamma t}), \quad (15)$$

where ω_{jk}^y is the K-vector of market capitalization weights of the countries in industry j .¹⁸

Panel A in Table 7 reports the time-series variances of the “pure” country effects and the cumulative sum of the industry effects in the 13 country portfolios, while Panel B reports the time-series variances of the pure industry effects and the cumulative sum of country effects in the 11 industry portfolios. In both cases, these variances are expressed as a ratio relative to the total variances of the excess returns. Their sum is therefore close, but not exactly one due to the presence of the extra covariance term in (13) and (15) between the industry and country effects.

Since country volatility does not vary greatly over the two states, to save space Table 7 simply presents results separately for the high and low industry volatility state. While a number of individual country and sector results are of interest in their own right, looking at the overall means, two findings stand out. First, the 3.3 percent figure reported in the upper right panel is the overall measure of the industry factor contribution in the low industry volatility state, which is well within the range previously estimated by Griffin and Karolyi (1998) (2 and 4 percent depending on the level of industry disaggregation—see tables 2 and 3 of their paper). Turning to the left panel, however, one can see that the same measure yields a much higher estimate of the aggregate industry component in the country portfolios (22.3 percent on average). In both the high and low industry volatility states, the average pure country volatility accounts for over 90 percent of the total country volatility—the fact that the right- and the left-hand side estimates in Panel A add to 120 percent being due to the higher negative covariance between the pure country and the composite industry effect during the high industry volatility state.

Moving to the breakdown of the industry portfolios shown in the bottom panels of Table 7, it is clear that the aggregate contribution of country effects to industry portfolios is also state sensitive, being much lower (17 percent) in the high industry volatility state than in the low industry volatility state where it more than doubles (41 percent). Similarly, the pure industry contribution accounts for 91 percent of the total industry portfolio volatility in the high industry volatility state but only for 69 percent in the low industry volatility state. These

¹⁸ These measures are slightly different from those reported in Griffin and Karolyi (1998) in that they account for inter-industry covariances (in (13)) and inter-country covariances (in (15)). However, the results are not very sensitive to modifying our formulas so that they are instead based on sums of variances of individual industry or country effects.

results therefore suggest that decomposition results reported in the existing literature vary considerably over economic states.

VI. IMPLICATIONS FOR GLOBAL PORTFOLIO DIVERSIFICATION

The above decompositions of systematic variance are based on the average country and industry variances. As such they are statistical measures that do not represent the payoffs from a portfolio investment strategy since they ignore covariances between the returns on the underlying country, industry and global equity portfolios. The advantage of such measures is that they provide a clear idea of the relative size of the variances of returns on the three components (global, industry and country). Investors, however, will be interested in economic measures of volatility and risk that represent feasible investment strategies and hence account for covariances between returns on the different portfolios involved. Moreover, changes in these covariances have potentially very important macroeconomic implications. For instance, when such covariances increase, domestic risk becomes less diversifiable what in turn tends to raise the equity premia on a variety of portfolios and drive up the overall cost of capital for firms.

The large literature on the links between national stock markets finds that the covariance of (excess) returns between national stock indices displays considerable variation over time (King, Sentana, and Wadhvani, 1994; Lin, Engle, and Ito, 1994; Longin and Solnik, 1995; Karolyi and Stultz, 1996; Bekaert and Harvey, 1997; Bekaert, Harvey, and Ng, 2003). In this section, we use firm level data and the methodology laid out in the previous sections to characterize the behavior of country portfolio covariances. Like King, Sentana, and Wadhvani (1994) and others, we let such time variation in country covariances be driven by an unobserved latent variable but, unlike those authors, we characterize such variations in terms of relatively lengthy historical periods or “states” and allow for differences in industry composition across countries to play a role. Likewise, the same approach is used to characterize the covariance patterns of the various industry portfolios. The respective estimates are presented in section 6.1. Using these estimates, variations in the volatility of investment strategies exposed to country- and industry risks are then examined in section 6.2.

A. Variations in Covariances Across States

The joint models ((9)—(10)) assume separate state processes for the global return factor (which affects all stocks in every period) and for the country or industry returns. Each of these state variables can be in the high or low volatility state. The return on a geographically diversified portfolio invested in industry j will be $\alpha_t + \beta_{jt}$, while the return on an industrially diversified country portfolio is $\alpha_t + \gamma_{kt}$. For such portfolios there are thus four possible state combinations. For example, for the industry portfolios the four states are:

- high industry volatility, high global volatility ($s_{\beta t} = 1$; $s_{\alpha t} = 1$)
- high industry volatility, low global volatility ($s_{\beta t} = 1$; $s_{\alpha t} = 2$)
- low industry volatility, high global volatility ($s_{\beta t} = 2$; $s_{\alpha t} = 1$)
- low industry volatility, low global volatility ($s_{\beta t} = 2$; $s_{\alpha t} = 2$)

The correlation between geographically diversified industry portfolios is likely to vary strongly according to the underlying combination of global and industry state variables. By construction, the global component is common to all stocks. Thus, when the global return variable is in the high volatility state, it will contribute relatively more to variations in the returns of such portfolios and correlations will increase. In contrast, when the global return component is in the low volatility state, correlations between country or industry portfolios will tend to be lower.

Similarly, when the industry component is in the low volatility state, the relative significance of the common global return component is larger so that correlations between industry portfolios will be stronger compared to when the industry return process is in the high volatility state. Given the very large differences between volatilities in the high and low volatility states observed for the global and industry portfolios, these effects are likely to give rise to large differences between correlations of geographically diversified industry portfolios in the four possible states.

A complication arises when computing these correlations as they depend on the correlation between the global and industry or country portfolio returns. Terms such as $Cov(\alpha_t, \gamma_{kt} | s_t, s_{\gamma_t})$ can be consistently estimated as follows:

$$\begin{aligned}
 Cov(\alpha_t, \beta_{jt} | s_{\alpha_t}, s_{\beta_{jt}}) &= \frac{\sum_{t=1}^T \pi_{s_{\alpha_t}} \pi_{s_{\beta_{jt}}} (\alpha_t - \hat{\alpha}_{s_{\alpha_t}}) (\beta_{jt} - \hat{\beta}_{s_{\beta_{jt}}})}{\sum_{t=1}^T \pi_{s_{\alpha_t}} \pi_{s_{\beta_{jt}}}}, \\
 Cov(\alpha_t, \gamma_{kt} | s_{\alpha_t}, s_{\gamma_t}) &= \frac{\sum_{t=1}^T \pi_{s_{\alpha_t}} \pi_{s_{\gamma_{kt}}} (\alpha_t - \hat{\alpha}_{s_{\alpha_t}}) (\gamma_{kt} - \hat{\gamma}_{s_{\gamma_t}})}{\sum_{t=1}^T \pi_{s_{\alpha_t}} \pi_{s_{\gamma_t}}}, \\
 Cov(\beta_{jt}, \gamma_{kt} | s_{\beta_{jt}}, s_{\gamma_t}) &= \frac{\sum_{t=1}^T \pi_{s_{\beta_{jt}}} \pi_{s_{\gamma_t}} (\beta_{jt} - \hat{\beta}_{s_{\beta_{jt}}}) (\gamma_{kt} - \hat{\gamma}_{s_{\gamma_t}})}{\sum_{t=1}^T \pi_{s_{\beta_{jt}}} \pi_{s_{\gamma_t}}}.
 \end{aligned} \tag{16}$$

To investigate just how different these correlations and volatilities are, Table 8 presents the estimated covariances and correlations in the four possible states for the industrially diversified country portfolios, while Table 9 presents the estimated covariances and correlations for the geographically diversified industry portfolios. Variances are presented on the diagonals, covariances above the diagonal and correlations below the diagonal.

For the country portfolios, some interesting findings emerge. First, correlations across countries vary substantially, even after allowing for cross-country differences in industry composition. In particular, correlations are generally higher among the Anglo-Saxon countries (notably between Canada, the United States, and the United Kingdom) and lowest between the United States and much of continental Europe and Japan. This result is

consistent with the evidence of other studies using different methodologies and measures (see, e.g., IMF, 2000) and our estimates show that it broadly holds across states.¹⁹ Second, correlations change markedly across states. Since there is not much difference between the variance of country returns in the high and low volatility states, the main driver of the results will be whether the global portfolio is in the high or low volatility state. The average correlation between the country portfolios is 0.30 in the low global volatility state and 0.56 in the high global volatility state. Thus, as other studies using a different methodology have found (see e.g. Solnik and Roulet, 2000; Bekaert and Harvey, 1997; Bekaert, Harvey, and Ng, 2003), the state process for the global return component clearly makes a big difference to the average correlations between the country portfolios – our estimates for mature markets indicating that such correlations almost double in the high volatility state.

Turning to the geographically diversified industry portfolios listed in Table 9, a richer picture emerges since the global high and low volatility states are now supplemented by the high and low industry volatility states. When the industry process is in the high volatility state while the global process is in the low volatility state, the average correlation across industry portfolios is only 0.19. This rises to 0.50 when the industry and global processes are both in the high volatility state or both are in the low volatility state. Finally, when the industry state process is in the low volatility state while the global process is in the high volatility state, the average correlation across the geographically diversified industry portfolios is 0.81.²⁰ These results show that the average correlations between geographically diversified industry portfolios vary substantially according to the state process driving the common industry component and the global component, with the non-negligible differences in industry factor correlations within each state being especially magnified in the high industry volatility state. Finally we note how different the average volatility level is in the high and low volatility states. For the country portfolios the variation in volatility is, unsurprisingly, somewhat smaller. The mean volatility is 6.4 percent per month in the high global volatility state and 5.3 percent in the low volatility state. The mean volatility of the industry portfolios is 6.6 percent per month in the high industry-, high global volatility state as compared with an average volatility of these portfolios of 3.6 percent in the low industry-, low global volatility state.

Significant economic consequences follow from these results. Generally, it will be much more difficult to diversify internationally or across industries when the global volatility process is in the high volatility state while the industry (country) process is in the low

¹⁹ Among continental European countries, a main exception is the Netherlands whose country factor volatility is highly correlated with those of the US and the UK. Much of this correlation, however, appears to reflect the behavior of one very large company (Shell) and the relative thinness of the Dutch country portfolio.

²⁰ Consistent with other findings in the literature, correlations between the industry portfolios are generally higher than the correlations between the country portfolios.

volatility state. This suggests that it is beneficial for investors to carefully keep track of the underlying state probabilities, particularly since the high persistence in the state probabilities implies considerable predictability of future states if the current state is reasonably precisely estimated.

B. Volatility of Portfolios Exposed to Country or Industry Risks

An alternative economic measure of the country, industry and global factors' contribution to portfolio variance can be derived by considering a simple portfolio investment strategy that tilts the industry or country weights in proportion with their market capitalization. To set up such a portfolio, we define $\omega_{\beta t}$ as market capitalization weights for the industries and $\omega_{\gamma t}$ as market capitalization weights for the countries. These are defined using beginning-of-month weights. Naturally, the weights sum to one in any given month, i.e., $\omega'_{\beta t} = \omega'_{\gamma t} = 1$.

The conditional variance of a portfolio tilted towards industries in proportion with their market capitalization weights can be expressed as:

$$\sum_{s_{\beta t}} \pi_{s_{\beta t}} \left\{ \omega'_{\beta t} \Omega_{\beta s_{\beta t}} \omega_{\beta t} + \left(\omega'_{\beta t} \mu_{\beta s_{\beta t}} - \bar{\mu}_{\beta t} \right)^2 \right\}, \quad (17)$$

where $\bar{\mu}_{\beta t} = \sum_{s_{\beta t}} \pi_{s_{\beta t}} (\omega'_{\beta t} \mu_{\beta s_{\beta t}})$ is the expected industry portfolio return averaged across states and across industries.

Similarly, the conditional variance of a portfolio tilted towards countries in proportion with their market capitalization weights is:

$$\sum_{s_{\gamma t}} \pi_{s_{\gamma t}} \left\{ \omega'_{\gamma t} \Omega_{\gamma s_{\gamma t}} \omega_{\gamma t} + \left(\omega'_{\gamma t} \mu_{\gamma s_{\gamma t}} - \bar{\mu}_{\gamma t} \right)^2 \right\}, \quad (18)$$

where $\bar{\mu}_{\gamma t} = \sum_{s_{\gamma t}} \pi_{s_{\gamma t}} (\omega'_{\gamma t} \mu_{\gamma s_{\gamma t}})$ is the expected country portfolio return averaged across states and across countries.

Figure 6 reports the time-series of these measures of risk. Clearly the industry tilts give rise to a much higher volatility when the industry state variable is in the high volatility state, i.e. around 1974, 1980, 1987 and again from 1998 onwards. At these points in time the volatility of the tilted industry portfolios is between 1 percent and 1.4 percent per month, whereas its typical level is much lower around 0.20 percent per month. For the tilted country portfolio, the normal volatility is around 0.60, but this rises to a higher level between 1 percent and 1.4 percent per month in 1978, 1981 and again in 1988. As expected, periods with high country volatility do not match up closely with the country states shown in Figure

3 since differences in volatility between these are not as pronounced as those found for the industry portfolios, c.f. Table 4.

Overall, these results demonstrate considerable time variation in the volatility of portfolios that are exposed to either country or industry risks. As such, they confirm the economic importance of accounting for regimes in common country and industry factors.

VII. CONCLUSION

This paper has presented a novel two-stage methodology to measuring the relative contribution of global, and country and industry specific factors to stock return volatility. In the first stage, the Heston and Rouwenhorst (1994, 1995) dummy factor model of decomposing stock returns into global, industry, and country-specific factors is used to create “pure” industry and “pure” country portfolios based on individual stock return data. Returns on these portfolios are then modeled individually or jointly as regime-switching processes in the second stage. We estimate the model using a global firm-level dataset spanning over three decades, which is more suitable to capture the time-varying nature of stock return dynamics than the much shorter firm-level datasets commonly employed in this literature. The results show that the proposed methodology not only fits the data better—with standard tests of model selection clearly rejecting the linear single regime specification commonly used in the literature—but also yields several key findings on the nature of stock return volatility.

First, for most countries and industries, there is very strong evidence of two regimes characterized by very different levels of volatility. Both regimes tend to be highly persistent, with high volatility states proving to be the least persistent. This inverse relationship between volatility and persistence across states is clearly expected and consistent with the findings of previous work such as Ang and Bekaert (2002) and Perez-Quiros and Timmermann (2000). On average, individual country estimates show that high volatility states have a duration of about 16 months, as opposed to 39 months for the low-volatility state, whereas the respective estimates for individual industry estimates are 22 and 48 months.

Second, there is evidence of a significant common dynamic component in the vector of country and industry portfolio returns. The common country component is shown to be by far the most persistent, possibly reflecting slowly evolving country factors related to institutional changes, whereas the lower persistence of the common industry component appears to reflect a variety of global shocks that affect industries very differently, such as oil price changes since the early 1970s and the boom and bust in information technology more recently. Consistent with this hypothesis, the common industry volatility is very different across states, being more than twice as high in the high-volatility state. Given these distinctive features of each state, the model is able to identify the timing of the various states for global, common country, and common industry components over the past thirty years showing, in particular, that the post-1997 period has been unique in the juxtaposition of a relatively long-lasting high industry and high global volatility state.

Third, in allowing for non-linear dynamics and providing evidence of two distinct states, our model yields arguably more precise estimates than earlier studies of the time-series variation in the contribution of country and industry factors to stock return variance. Our estimates indicate that global and industry factors have increased in significance relative to the country factors since the late 1990s and that, in the recent state, the industry factor accounts for about one-third of total systematic (or non-idiosyncratic) variance in stock returns. Over the whole sample 1973–2002, we also show that the industry contribution has averaged some 10 percent—a figure that justifies earlier studies’ emphasis on the importance of country as compared with industry diversification strategies.

Last but not least, the paper shows that these results have important implications for global risk diversification and portfolio management strategies. As discussed above, with the estimation of two states per factor, eight possible combinations arise. In general, the correlations among the various country and industry portfolios are shown to be considerably stronger in the high global volatility state than in the low global volatility state. In the case of industrially diversified country-specific portfolios, those correlations nearly double in the high volatility state on average, so the benefits of investing abroad tend to be considerably more meager when global volatility is high. Moreover, pair-wise correlations between the various country portfolios indicate that such benefits are even smaller when international diversification is confined to Anglo-Saxon countries or within continental Europe—a finding consistent with the recent literature on the “geography view” of financial markets. Conversely, international diversification is clearly beneficial when global volatility is low, and one tangible manifestation of this was the massive wave of cross-border equity flows in the period 1991-97, before its downturn during the current high global volatility state. Finally, our estimates show that when global and industry-specific volatility are both in a high state, investors benefit more from diversifying across industries than along country lines.

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Figure 1.A. Smoothed State Probabilities for Individual Countries
(High Volatility State)

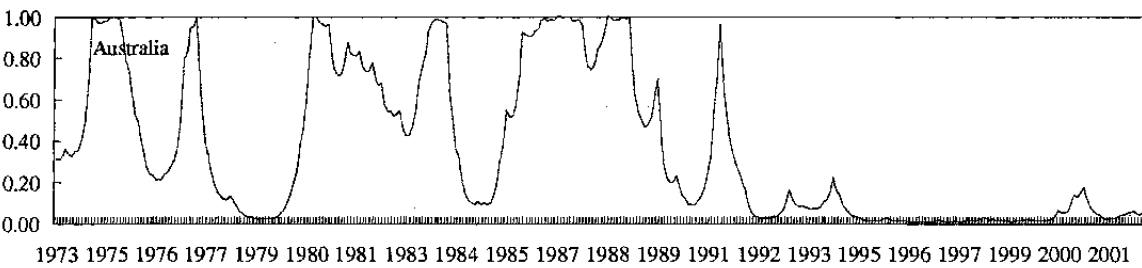
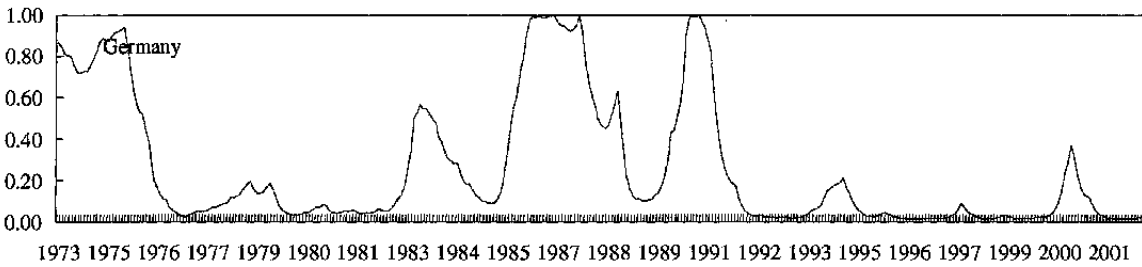
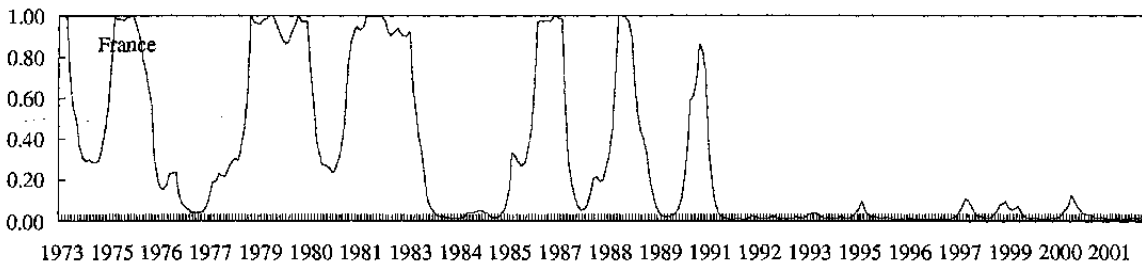
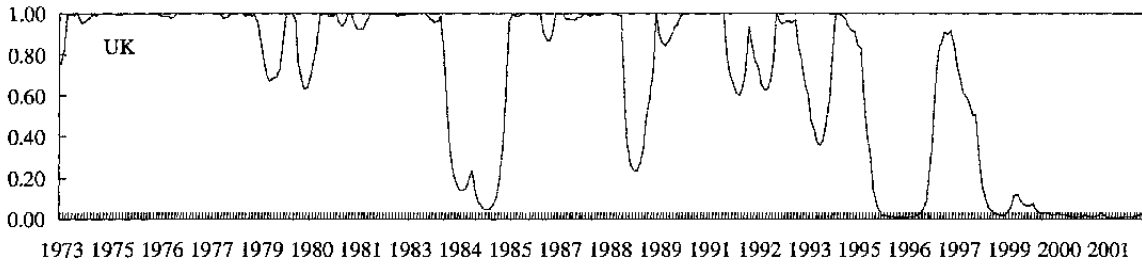
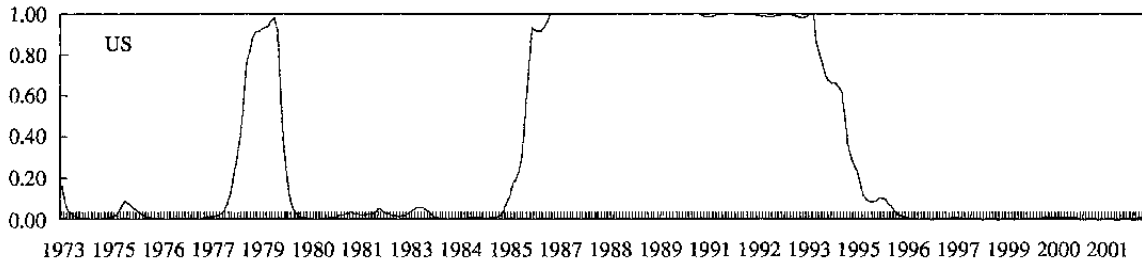


Figure 1.B. Smoothed State Probabilities for Individual Countries
(High Volatility State)

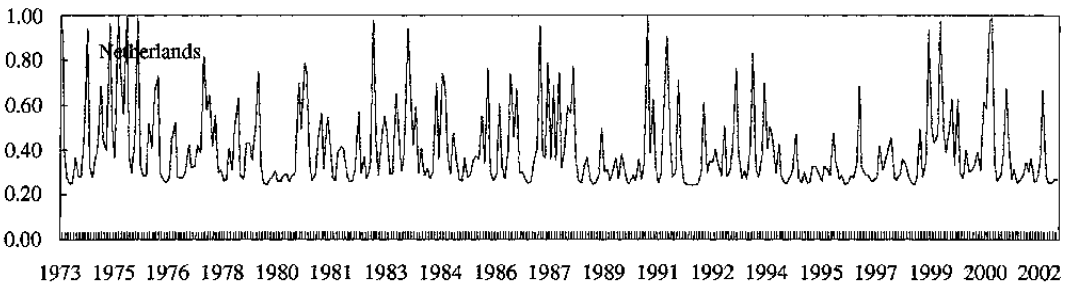
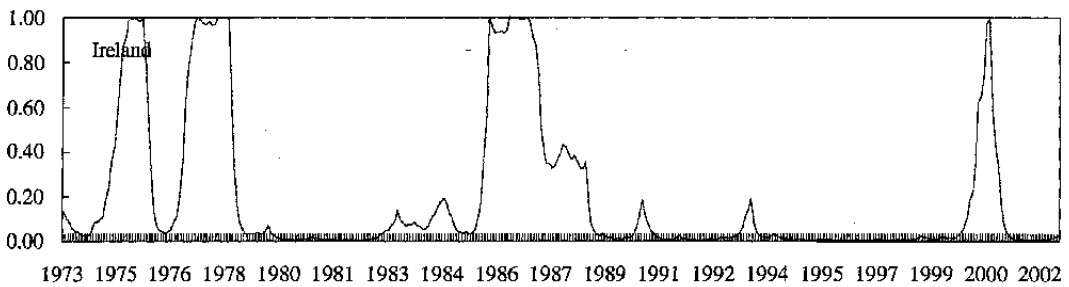
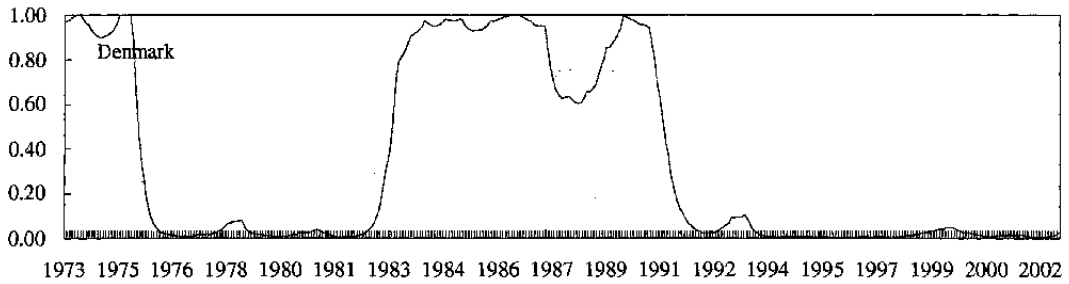
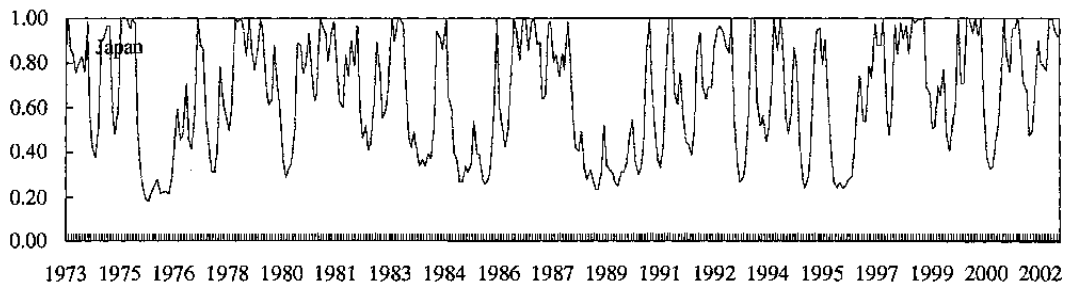
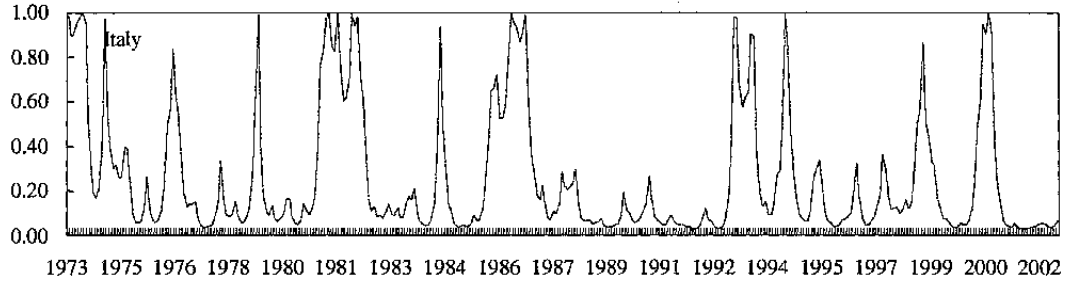


Figure 2.A. Smoothed State Probabilities for Individual Industries
(High Volatility State)

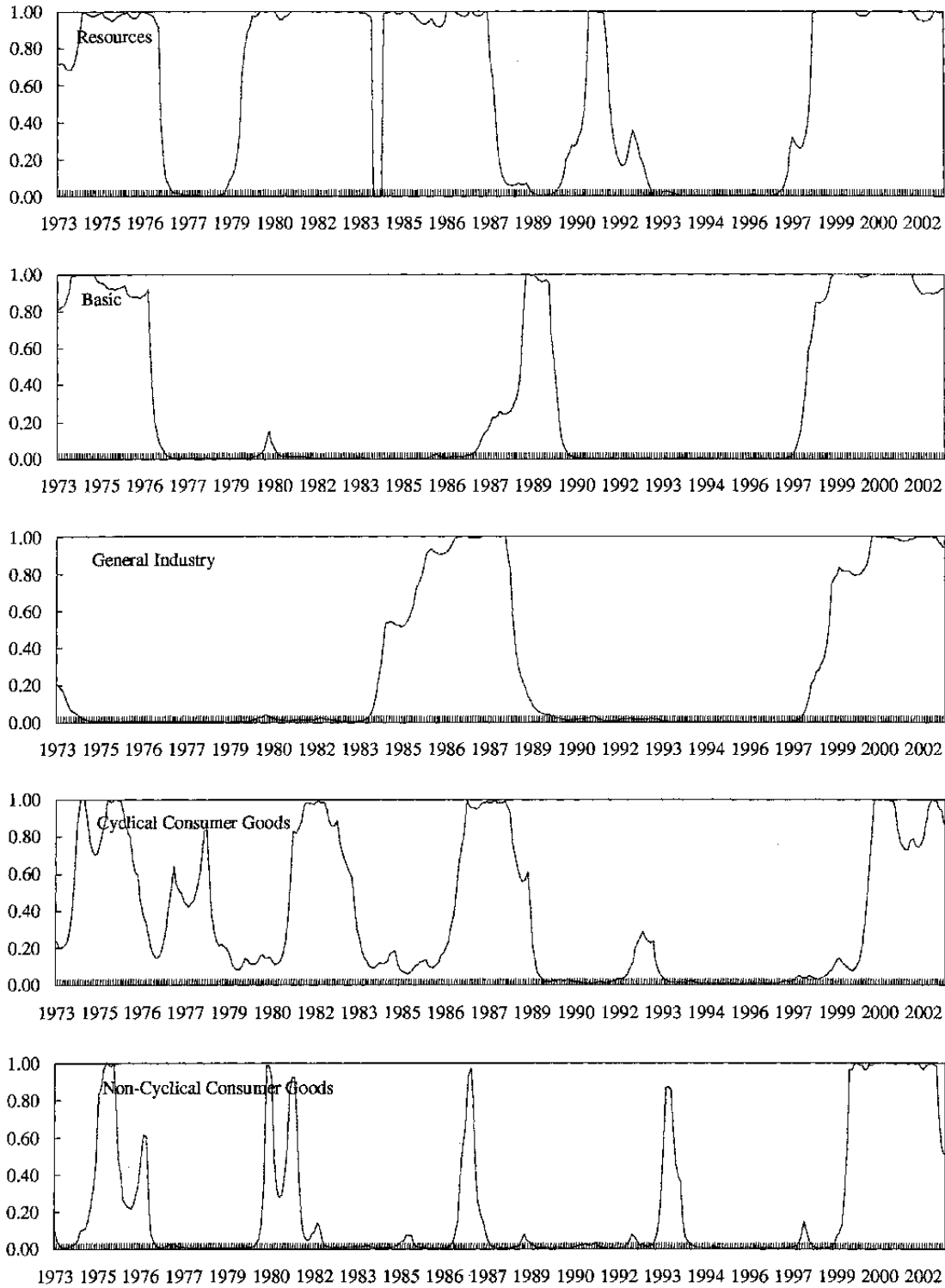


Figure 2.B. Smoothed State Probabilities for Individual Industries
(High Volatility State)

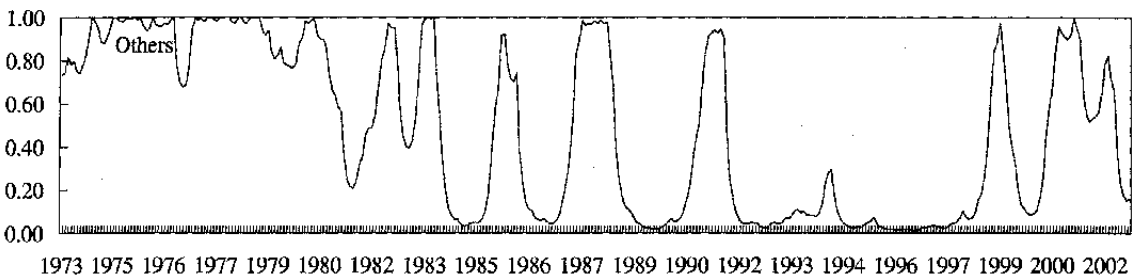
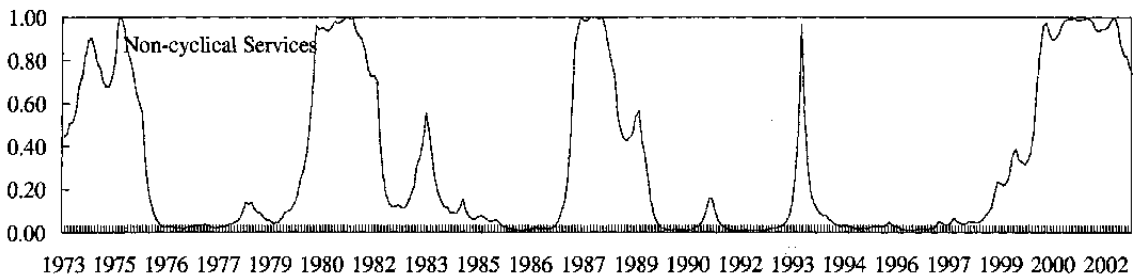
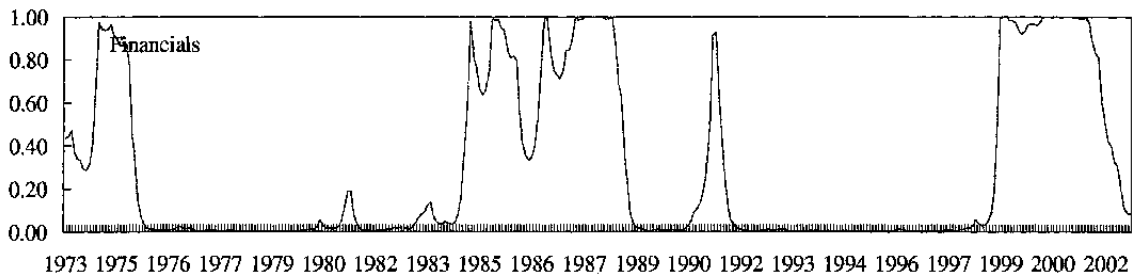
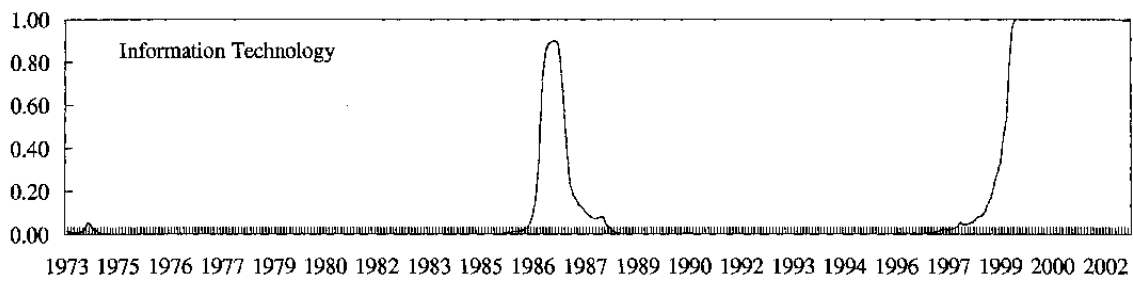
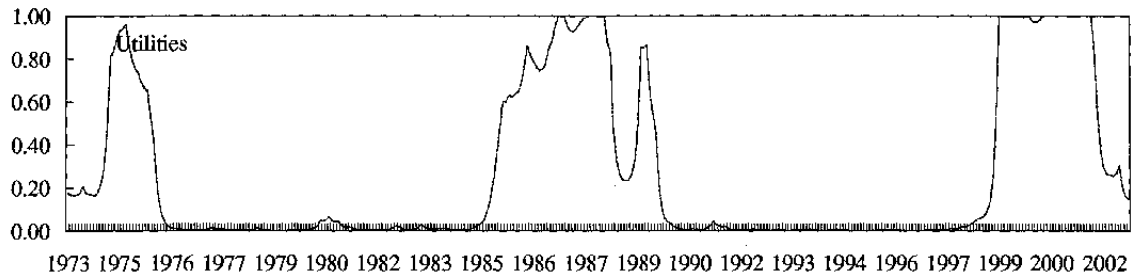


Figure 3. Smoothed State Probabilities for Common Components
(High Volatility State)

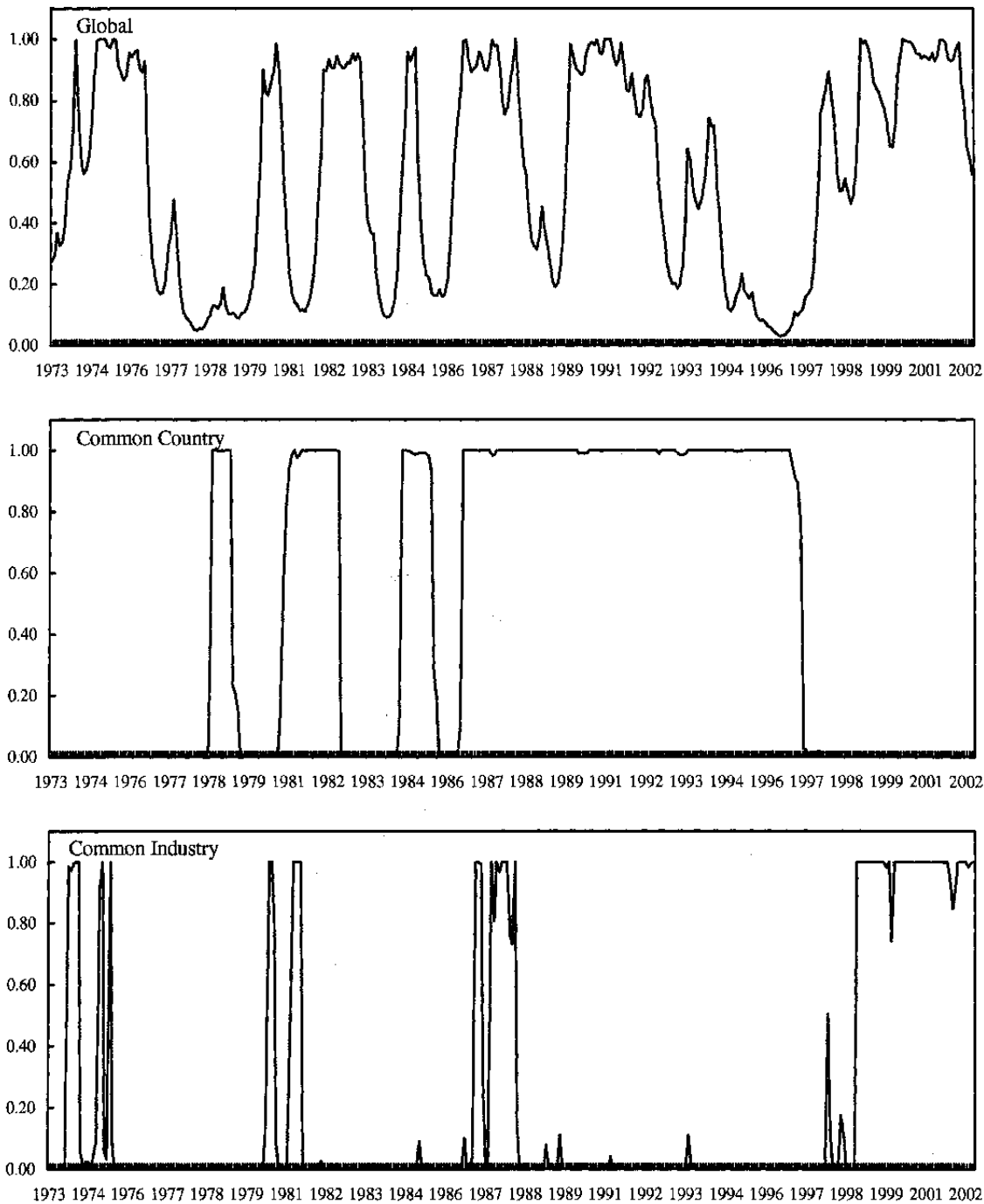


Figure 4. Systematic Volatility

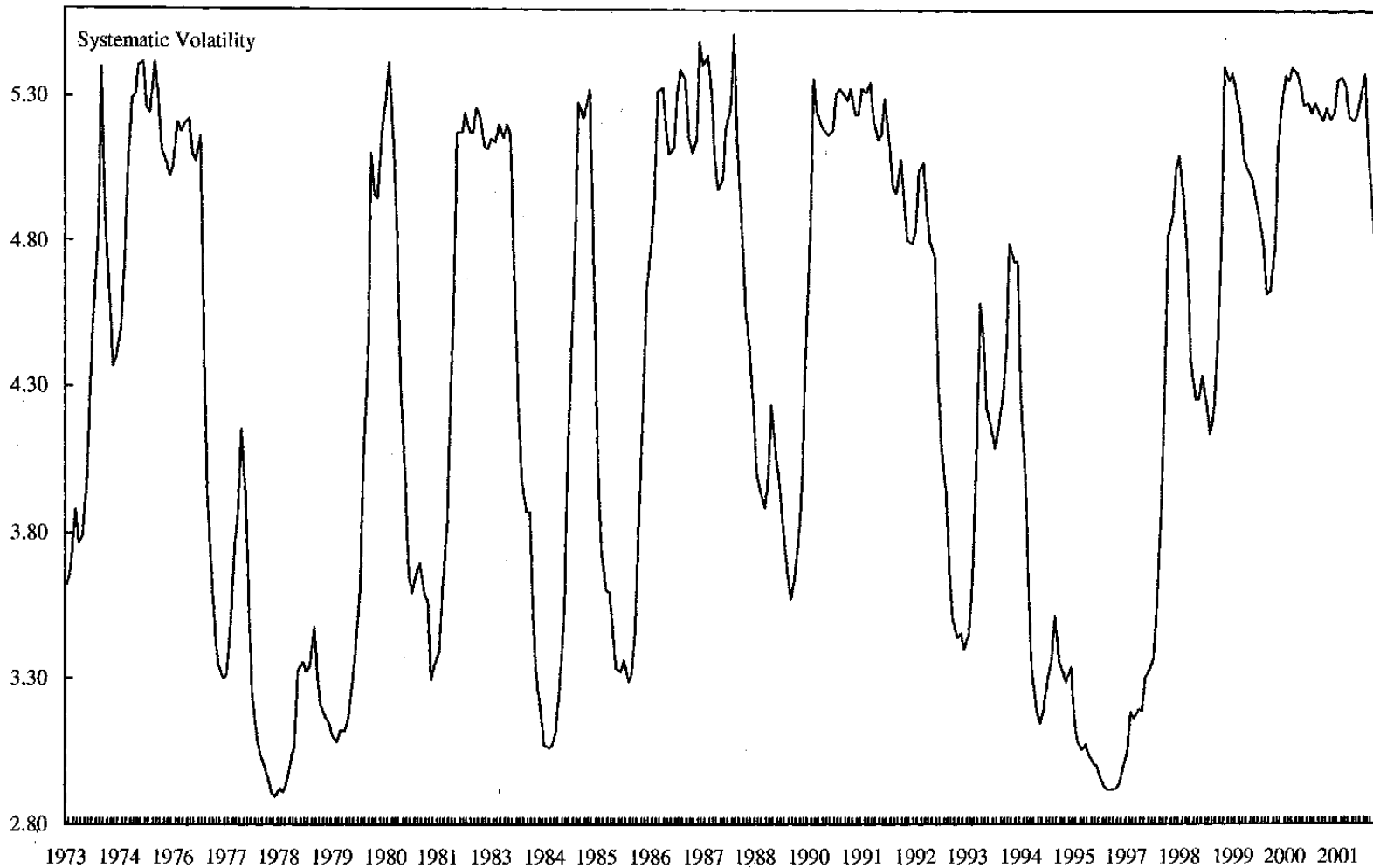


Figure 5. Decomposition of Systematic Variance into Country, Industry and Global Components

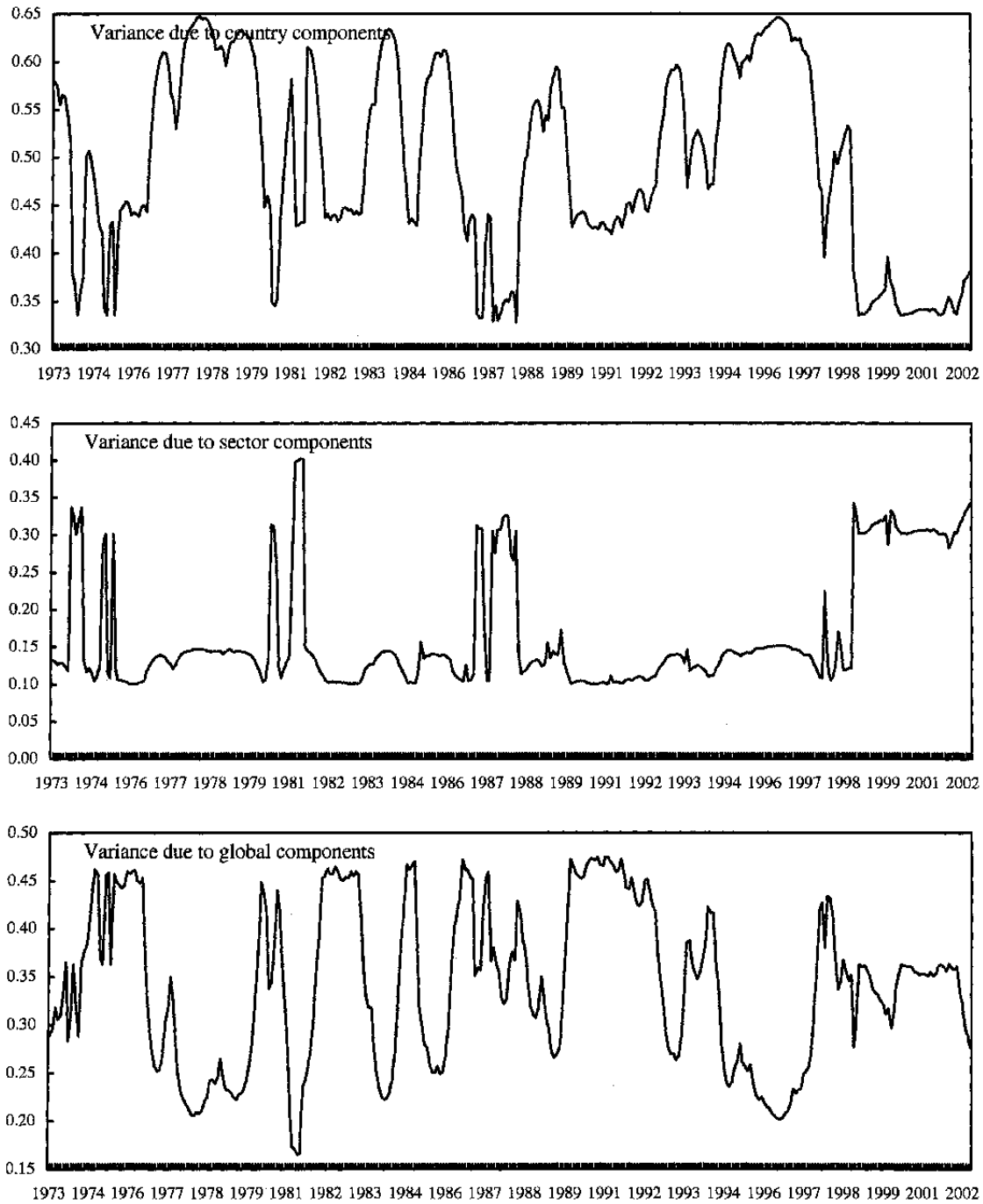


Figure 6. Volatility from Shifting Industry or Country Weights

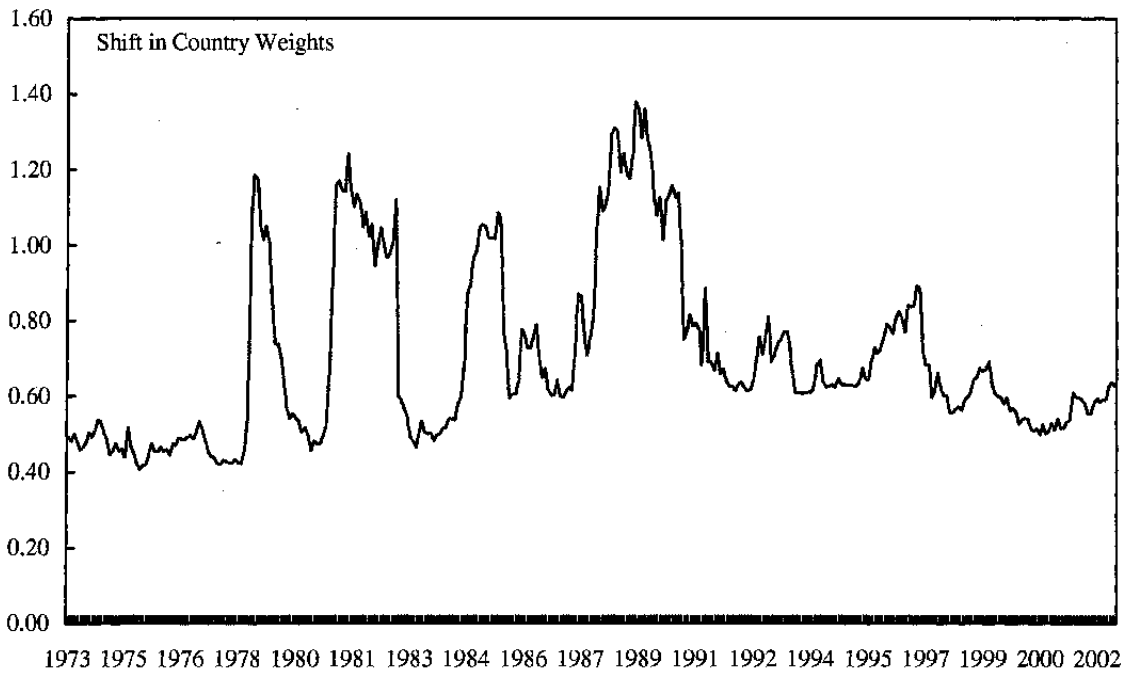
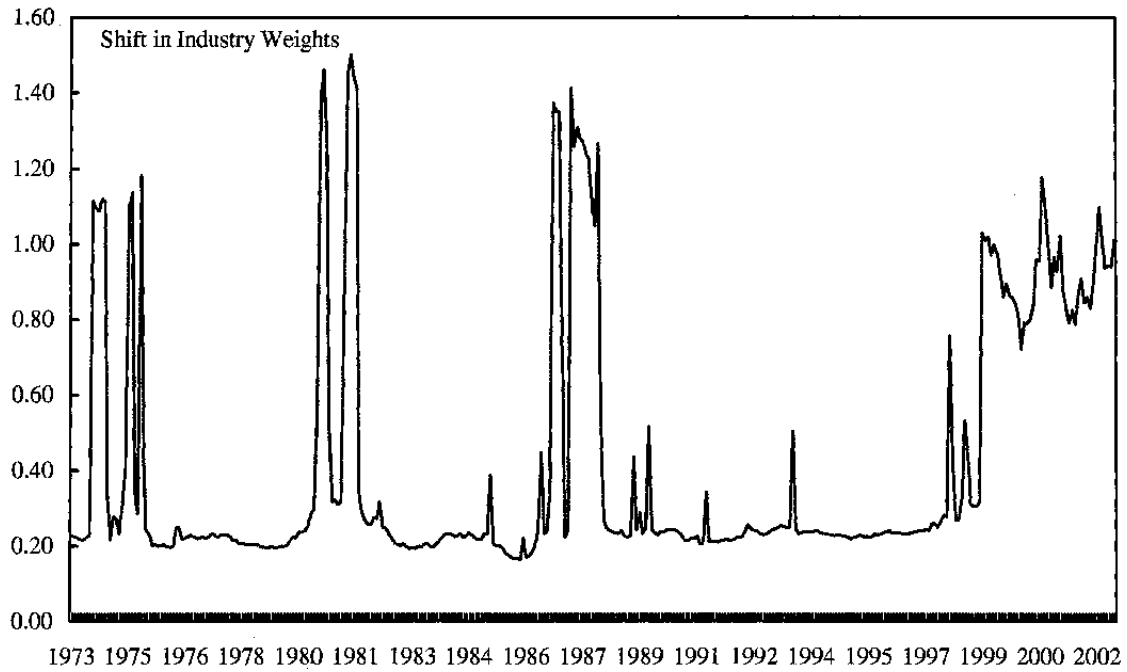


Table 1: Summary Statistics for the Country, Industry, and World Portfolio Returns

	mean	s.d.	skew	kurtosis
A. Country portfolios				
US	-0.12	2.77	-0.42	2.48
UK	0.07	5.07	1.81	14.8
France	0.10	5.25	0.27	1.32
Germany	-0.29	5.02	-0.09	0.81
Italy	-0.12	7.28	0.38	1.71
Japan	0.11	4.63	0.02	0.58
Canada	-0.29	3.85	-0.34	0.55
Australia	-0.15	6.27	-0.25	1.67
Belgium	-0.22	4.65	0.60	1.87
Denmark	-0.10	5.32	0.33	1.33
Ireland	0.18	6.11	0.55	2.72
Netherlands	-0.12	3.31	-0.04	1.02
Switzerland	-0.28	4.04	-0.02	0.09
Average	-0.09	4.89	0.22	2.38
B. Industry portfolios				
Resources	-0.12	3.74	0.03	0.88
Basic	-0.19	2.52	0.06	3.71
General industry	-0.05	1.78	-0.40	1.24
Cyclical durables	-0.09	3.24	-0.30	1.22
Non-cycl. durables	-0.05	2.45	-0.51	4.27
Cyclical services	-0.06	1.61	0.01	0.68
Non-cycl. Services	-0.17	3.72	0.88	3.11
Utilities	-0.28	4.07	0.93	6.46
Information technology	0.18	4.34	0.50	3.01
Financials	0.00	2.28	-0.16	4.78
Others	-0.51	2.79	0.21	2.62
Average	-0.12	2.96	0.11	2.91
C. World:	1.71	4.34	-0.04	0.79

Notes: This table reports descriptive statistics for the country, industry and global portfolios using the decomposition (2) subject to the constraints (3), (4). Returns are measured at the monthly frequency over the period February 1973 – February 2002 and are based on a data set covering up to 3,951 firms in developed stock markets.

Table 2: Tests for Multiple States

A. Country Portfolios							
	US	UK	France	Germany	Italy	Japan	Canada
p-value	0.000	0.000	0.000	0.004	0.000	0.005	0.352
	Australia	Belgium	Denmark	Ireland	Netherlands	Switzerland	
p-value	0.000	0.000	0.000	0.000	0.071	0.341	
B. Industry Portfolios							
	Resources	Basic	General ind.	Cyc. cons. goods	Non-cyc. Cons.	Cyc. serv.	Non-cyc. serv.
p-value	0.006	0.000	0.000	0.000	0.000	0.271	0.000
	Utilities	Inf. Technology	Financials	Other			
p-value	0.000	0.000	0.000	0.000			
C. Global Factor							
p-value	0.000						

Notes: This table reports Davies' (1977) p-values for the test of a single state, accounting for unidentified nuisance parameters under the null hypothesis of a single state. P-values below 0.05 indicate the presence of more than one state.

Table 3: Selection Criteria for Individual Country, Industry, and Global Portfolios

	AIC			BIC			H-Q		
	k = 1	k = 2	k = 3	k = 1	k = 2	k = 3	k = 1	k = 2	k = 3
A. Country Portfolios									
US	4.882	4.700	4.728	4.904	4.767	4.860	4.891	4.727	4.780
UK	6.093	5.803	5.720	6.115	5.869	5.852	6.101	5.829	5.773
France	6.163	6.045	6.050	6.185	6.111	6.182	6.172	6.071	6.102
Germany	6.074	6.049	6.069	6.096	6.115	6.201	6.083	6.075	6.121
Italy	6.817	6.731	6.750	6.839	6.798	6.882	6.826	6.758	6.802
Japan	5.910	5.886	5.894	5.932	5.952	6.027	5.919	5.912	5.947
Canada	5.543	5.549	5.559	5.565	5.615	5.693	5.552	5.575	5.613
Australia	6.518	6.435	6.455	6.540	6.501	6.587	6.526	6.461	6.508
Belgium	5.920	5.856	5.861	5.942	5.923	5.994	5.928	5.883	5.914
Denmark	6.189	6.133	6.151	6.211	6.199	6.284	6.197	6.160	6.204
Ireland	6.468	6.327	6.306	6.490	6.393	6.438	6.477	6.354	6.359
Netherlands	5.241	5.235	5.250	5.263	5.301	5.383	5.250	5.261	5.303
Switzerland	5.640	5.646	5.660	5.663	5.712	5.793	5.649	5.672	5.713
B. Industry Portfolios									
Resources	5.485	5.462	5.356	5.507	5.528	5.488	5.493	5.488	5.409
Basic	4.697	4.514	4.490	4.719	4.581	4.623	4.706	4.541	5.543
General industry	4.000	3.893	3.907	4.022	3.959	4.040	4.009	3.920	3.960
Cyclical consumer goods	5.200	5.120	5.110	5.222	5.185	5.242	5.209	5.145	5.163
Non-cyclical consumer goods	4.638	4.340	4.359	4.660	4.407	4.492	4.647	4.367	4.412
Cyclical services	3.795	3.798	3.768	3.817	3.865	3.900	3.803	3.825	3.821
Non-cyclical services	5.473	5.396	5.373	5.495	5.462	5.506	5.482	5.422	5.426
Utilities	5.653	5.448	5.463	5.675	5.514	5.595	5.662	5.474	5.516
Information technology	5.783	5.484	5.460	5.805	5.550	5.593	5.792	5.510	5.513
Financials	4.494	4.225	4.224	4.513	4.292	4.357	4.500	4.252	4.277
Others	4.898	4.809	4.822	4.921	4.875	4.954	4.907	4.835	4.875
C. Global									
	5.781	5.741	5.749	5.803	5.808	5.881	5.790	5.768	5.802

Notes: This table shows the values of various information criteria used to determine whether a single-state ($k = 1$), a two-state ($k = 2$), or a three-state ($k = 3$) model is chosen for the country, industry and global portfolios. AIC gives the value of the Akaike information criterion, BIC the Schwarz's Bayesian information criterion and HQ the Hannan-Quinn information criterion. Lowest values (in bold) should be preferred.

Table 4: Estimation Results for the Univariate Markov Switching Models

	Volatility		Stayer Prob.		Ergodic Prob.		Duration	
	State 1	State 2	State 1	State 2	State 1	State 2	State 1	State 2
A. Country Portfolios								
US	3.95	1.87	0.98	0.99	0.33	0.68	41.30	85.80
UK	11.10	3.60	0.83	0.98	0.11	0.89	6.00	49.00
France	7.66	3.66	0.91	0.97	0.28	0.72	11.50	29.50
Germany	6.86	4.16	0.93	0.98	0.24	0.76	13.40	43.50
Italy	10.93	5.16	0.76	0.92	0.26	0.75	4.10	12.00
Japan	5.45	2.32	0.84	0.69	0.65	0.35	6.10	3.20
Canada	4.70	3.14	0.63	0.79	0.36	0.64	2.70	4.76
Australia	8.63	4.39	0.93	0.96	0.36	0.65	13.30	24.24
Belgium	7.78	3.91	0.64	0.96	0.10	0.90	2.80	25.90
Denmark	7.07	4.15	0.97	0.99	0.27	0.73	35.50	97.70
Ireland	9.83	4.58	0.90	0.98	0.19	0.81	10.30	43.30
Netherlands	4.31	2.40	0.48	0.65	0.40	0.60	1.90	2.90
Switzerland	4.58	3.41	0.98	0.99	0.40	0.60	56.48	84.48
Average	7.14	3.60	0.83	0.91	0.30	0.70	15.80	38.94
B. Industry Portfolios								
Resources	3.32	2.88	0.96	0.62	0.90	0.10	23.60	2.60
Basic	3.74	1.74	0.97	0.99	0.69	0.31	35.70	80.00
General industry	2.55	1.37	0.98	0.99	0.33	0.67	47.20	95.60
Cyclical cons. goods	4.42	2.31	0.94	0.96	0.38	0.62	16.40	26.90
Non-cycl. Cons. goods	4.32	1.55	0.90	0.97	0.22	0.78	10.20	35.50
Cyclical services	1.51	1.45	0.55	0.92	0.15	0.85	2.20	12.98
Non-cycl. Services	5.27	2.71	0.93	0.97	0.32	0.68	13.60	28.60
Utilities	6.43	2.75	0.95	0.98	0.26	0.74	18.70	52.70
Information technology	8.45	3.08	0.98	0.99	0.24	0.76	44.50	141.40
Financials	3.61	1.39	0.93	0.97	0.28	0.72	14.10	35.90
Others	3.60	1.71	0.93	0.94	0.47	0.53	14.40	16.00
Average	4.36	2.12	0.91	0.94	0.39	0.61	21.87	48.02

Notes: This table reports maximum likelihood estimates of the parameters of the regime switching model (6), (7) fitted to the individual country, industry and global portfolios. The stayer probabilities give the probabilities of remaining in states 1 and 2, respectively. Ergodic probabilities provide the average time spent in the two states, while the state durations are the average time spent without exiting from the states (in months).

Table 5: Other Estimation Results for the Common Component Models

	Stayer Prob.		Ergodic Prob.		Duration		Davies test
	State 1	State 2	State 1	State 2	State 1	State 2	
Country	0.975	0.976	0.486	0.514	40.1	42.5	0.0000
Industry	0.870	0.962	0.226	0.774	7.7	26.4	0.0000
Global	0.922	0.899	0.565	0.435	12.9	9.9	0.0004

Notes: This table reports maximum likelihood estimates of the transition probability parameters of the regime switching model (9), (10) fitted to the common state model for countries, industries or the global portfolio. The state transition probabilities give the probabilities of remaining in state 1 and state 2, respectively. Steady state or ergodic probabilities provide the average time spent in the two states, while the state durations are the average time spent without exiting from the states (in months). The Davies test is for the null of a single state versus the alternative of multiple states.

Table 6: Volatility Estimates for the Common Component Models

A. Common country component			B. Common industry component			C. Global component	
	State 1	State 2		State 1	State 2	State 1	State 2
US	3.47	1.85	Resources	5.66	2.99	5.27	2.67
UK	3.76	6.04	Basic	3.96	1.95		
France	5.54	4.94	General industry	2.60	1.47		
Germany	5.14	4.84	Cyclical consumer goods	4.80	2.62		
Italy	7.56	6.99	Non-cyclical consumer goods	4.25	1.62		
Japan	4.46	4.76	Cyclical services	2.01	1.46		
Canada	3.92	3.75	Non-cyclical services	5.65	2.98		
Australia	6.39	6.13	Utilities	6.69	2.97		
Belgium	4.90	4.38	Information technology	7.41	2.99		
Denmark	5.14	5.46	Financials	3.70	1.68		
Ireland	5.32	6.75	Others	2.76	2.79		
Netherlands	3.01	3.56					
Switzerland	4.16	3.89					
Average	4.88	4.95	Average	4.67	2.27		

Notes: This table reports maximum likelihood estimates of the volatility parameters of the regime switching model (9), (10) fitted to the common state model for countries or industries. The models thus extract a nonlinear state-variable common across the country or across the industry portfolios.

Table 7. Relative Contribution of "Pure" Country and Industry Factors to the Variance of Stock Returns

	High Industry Volatility State		Low Industry Volatility State	
	Pure Country	Acc. Industry	Pure Country	Acc. Industry
A. Country Portfolios				
US	0.955	0.091	0.992	0.011
UK	0.825	0.169	1.010	0.020
France	1.297	0.114	1.003	0.009
Germany	0.983	0.153	1.023	0.017
Italy	0.988	0.102	1.014	0.014
Japan	0.969	0.112	1.028	0.012
Canada	0.907	0.213	1.020	0.029
Australia	0.956	0.212	0.993	0.039
Belgium	1.092	0.300	1.028	0.033
Denmark	1.008	0.115	1.033	0.025
Ireland	0.922	0.227	1.053	0.026
Netherlands	0.626	0.471	0.973	0.107
Switzerland	0.971	0.438	1.033	0.049
Average	0.974	0.223	1.018	0.033
B. Industry Portfolios				
Resources	0.920	0.161	0.725	0.453
Basic	0.928	0.080	0.721	0.254
General industry	0.621	0.101	0.684	0.346
Cyclical cons. goods	1.168	0.114	0.941	0.309
Non-cycl. Cons. goods	0.772	0.138	0.435	0.532
Cyclical services	0.532	0.182	0.594	0.384
Non-cycl. Services	1.370	0.221	0.708	0.410
Utilities	1.345	0.060	0.894	0.200
Information technology	0.895	0.059	0.667	0.270
Financials	1.104	0.128	0.726	0.409
Others	0.349	0.647	0.511	0.923
Average	0.910	0.172	0.691	0.408

Notes: Panel A of this table shows the contribution of the "pure" country effect and the cumulated industry effect of the excess return (computed relative to the global return) on the individual country portfolios, using the decomposition (13) in the paper. Panel B shows the contribution of the "pure" industry effect and the cumulated country effect of the excess return (computed relative to the global return) on the individual industry portfolios using the decomposition (15) in the paper. The reported figures are ratios of the variance of each component to the variance of their sum (including their covariance).

Table 8. Covariances and Correlations for Industrially Diversified Country Portfolios

A. High Global Volatility State													
	US	UK	FR	GE	IT	JP	CA	AU	BE	DE	IR	NL	SW
US	22.576	21.077	15.481	11.452	12.418	17.511	17.049	16.616	14.321	9.494	20.049	15.753	13.538
UK	0.680	42.534	27.334	23.382	27.582	34.702	20.993	28.034	23.429	20.678	34.213	26.123	24.956
FR	0.445	0.572	53.637	29.912	30.362	36.561	13.863	17.861	28.936	18.813	30.921	22.389	24.173
GE	0.396	0.589	0.671	37.004	22.264	24.403	11.308	14.962	24.821	17.703	24.479	22.563	24.964
IT	0.297	0.481	0.471	0.416	77.383	35.471	16.039	18.271	20.623	20.757	27.111	19.699	16.904
JP	0.435	0.628	0.589	0.473	0.476	71.849	19.028	23.817	27.291	22.830	37.472	25.221	28.139
CA	0.755	0.677	0.398	0.391	0.384	0.472	22.585	23.058	13.024	10.860	20.533	14.562	13.595
AU	0.478	0.587	0.333	0.336	0.284	0.384	0.663	53.595	17.724	14.038	26.122	16.256	18.154
BE	0.490	0.584	0.642	0.663	0.381	0.523	0.445	0.394	37.846	16.177	30.436	20.627	21.922
DE	0.357	0.566	0.458	0.519	0.421	0.481	0.408	0.342	0.469	31.414	24.927	14.033	18.109
IR	0.559	0.695	0.559	0.533	0.408	0.585	0.572	0.472	0.655	0.589	57.045	25.005	26.657
NL	0.698	0.843	0.643	0.780	0.471	0.626	0.645	0.467	0.706	0.527	0.697	22.585	20.626
SW	0.507	0.681	0.588	0.731	0.342	0.591	0.509	0.442	0.635	0.575	0.629	0.773	31.528
B. Low Global Volatility State													
	US	UK	FR	GE	IT	JP	CA	AU	BE	DE	IR	NL	SW
US	13.810	6.208	4.145	2.405	-0.085	-5.585	9.836	8.909	4.076	3.354	4.321	6.349	3.141
UK	0.360	21.562	9.896	8.233	8.976	5.504	7.678	14.224	7.082	8.436	12.383	10.616	8.456
FR	0.177	0.338	39.733	18.296	15.290	10.896	4.081	7.584	16.122	10.104	12.625	10.416	11.207
GE	0.123	0.337	0.552	27.676	9.480	1.026	3.815	6.974	14.295	11.282	8.472	12.878	14.286
IT	-0.003	0.247	0.310	0.230	61.143	8.638	5.090	6.826	6.641	10.880	7.647	6.558	2.770
JP	-0.256	0.202	0.295	0.033	0.188	34.422	-2.514	1.780	2.717	2.359	7.415	1.487	3.411
CA	0.643	0.402	0.157	0.176	0.158	-0.104	16.926	16.904	4.333	6.273	6.360	6.712	4.751
AU	0.350	0.447	0.176	0.193	0.127	0.044	0.600	46.947	8.538	8.956	11.454	7.911	8.816
BE	0.215	0.298	0.500	0.532	0.166	0.091	0.206	0.244	26.123	8.558	13.230	9.745	10.046
DE	0.171	0.344	0.303	0.406	0.263	0.076	0.289	0.247	0.317	27.899	11.825	7.255	10.337
IR	0.198	0.455	0.342	0.275	0.167	0.216	0.264	0.285	0.442	0.382	34.357	8.640	9.299
NL	0.482	0.646	0.467	0.691	0.237	0.072	0.461	0.326	0.538	0.388	0.416	12.543	9.591
SW	0.191	0.412	0.403	0.615	0.080	0.132	0.261	0.291	0.445	0.443	0.359	0.613	19.500

Notes: This table reports estimates of the covariances and correlations between the returns on industrially diversified country portfolios. Results are shown for two states: high global volatility and low global volatility. Numbers above the diagonal show covariance estimates, numbers on the diagonal show variance estimates, while numbers below the diagonal are estimates of the correlations.

Table 9. Covariances and Correlations for Geographically Diversified Industry Portfolios

A. High Global Volatility, High Industry Volatility

	RESOR	BASIC	GENIN	CYCGD	NCYCG	CYSER	NCYSR	UTILS	ITECH	FINAN	OTHER
RESOR	44.698	27.487	23.026	17.816	10.006	17.214	7.179	5.569	22.755	23.987	26.029
BASIC	0.656	39.249	31.117	34.581	15.977	26.676	11.502	6.966	31.720	32.248	29.707
GENIN	0.566	0.816	37.092	36.960	15.375	29.660	13.931	1.763	53.177	28.895	33.892
CYCGD	0.359	0.744	0.818	54.976	13.293	33.825	16.511	3.227	53.585	32.844	32.822
NCYCG	0.335	0.571	0.565	0.401	19.964	13.737	5.309	2.977	18.766	20.295	17.400
CYSER	0.460	0.760	0.869	0.814	0.549	31.385	18.934	2.281	49.845	27.364	29.477
NCYSR	0.164	0.280	0.349	0.340	0.181	0.516	42.880	-3.578	39.028	15.932	18.059
UTILS	0.165	0.220	0.057	0.086	0.132	0.080	-0.108	25.634	-2.995	13.503	6.295
ITECH	0.302	0.449	0.774	0.640	0.372	0.788	0.528	-0.052	127.348	34.300	52.537
FINAN	0.553	0.793	0.731	0.682	0.700	0.753	0.375	0.411	0.468	42.131	31.869
OTHER	0.607	0.739	0.867	0.690	0.607	0.820	0.430	0.194	0.725	0.765	41.205

B. Low Global Volatility, High Industry Volatility

	RESOR	BASIC	GENIN	CYCGD	NCYCG	CYSER	NCYSR	UTILS	ITECH	FINAN	OTHER
RESOR	46.513	18.019	12.537	2.633	7.887	7.772	2.058	13.734	-3.558	12.519	14.541
BASIC	0.614	18.496	9.344	8.113	2.574	5.949	-4.904	3.846	-5.876	9.496	6.935
GENIN	0.486	0.575	14.299	9.472	0.951	7.912	-3.495	-2.377	14.560	5.122	10.099
CYCGD	0.081	0.395	0.525	22.793	-5.826	7.382	-5.610	-5.607	10.273	4.376	4.334
NCYCG	0.310	0.160	0.067	-0.327	13.911	0.360	-3.747	7.207	-11.482	4.892	1.977
CYSER	0.349	0.423	0.640	0.473	0.030	10.684	2.553	-0.813	12.274	4.638	6.731
NCYSR	0.054	-0.205	-0.167	-0.212	-0.181	0.141	30.820	-2.350	5.778	-2.474	-0.367
UTILS	0.318	0.141	-0.099	-0.185	0.305	-0.039	-0.067	40.148	-22.958	8.384	1.156
ITECH	-0.061	-0.160	0.451	0.252	-0.361	0.440	0.122	-0.424	72.907	-5.297	12.921
FINAN	0.440	0.530	0.325	0.220	0.315	0.340	-0.107	0.317	-0.149	17.379	7.097
OTHER	0.526	0.398	0.659	0.224	0.131	0.508	-0.016	0.045	0.374	0.420	16.413

Table 9 (concluded)

C. High Global Volatility, Low Industry Volatility

	RESOR	BASIC	GENIN	CYCGD	NCYCG	CYSER	NCYSR	UTILS	ITECH	FINAN	OTHER
RESOR	31.884	26.284	25.658	23.047	23.764	24.252	21.415	22.257	23.168	26.389	27.509
BASIC	0.780	35.637	31.534	28.314	28.892	31.026	24.000	24.962	29.079	31.083	32.749
GENIN	0.802	0.932	32.124	29.490	27.954	29.377	23.803	23.397	29.971	29.746	31.505
CYCGD	0.712	0.827	0.908	32.856	25.744	27.587	21.918	20.924	28.233	27.378	28.885
NCYCG	0.770	0.886	0.903	0.822	29.852	28.563	23.448	23.840	26.034	29.241	29.386
CYSER	0.767	0.928	0.925	0.859	0.933	31.386	23.516	24.143	27.393	30.539	30.651
NCYSR	0.709	0.752	0.786	0.715	0.803	0.785	28.582	22.515	22.197	24.652	25.210
UTILS	0.730	0.774	0.764	0.676	0.808	0.798	0.780	29.187	19.911	26.108	26.343
ITECH	0.684	0.812	0.882	0.822	0.795	0.816	0.692	0.615	35.947	27.480	29.220
FINAN	0.802	0.893	0.901	0.820	0.918	0.935	0.791	0.829	0.786	33.964	31.948
OTHER	0.771	0.868	0.879	0.797	0.851	0.865	0.746	0.771	0.771	0.867	39.976

D. Low Global Volatility, Low Industry Volatility

	RESOR	BASIC	GENIN	CYCGD	NCYCG	CYSER	NCYSR	UTILS	ITECH	FINAN	OTHER
RESOR	14.969	5.969	6.483	5.174	4.980	5.283	4.824	5.173	5.590	6.563	7.373
BASIC	0.447	11.922	8.959	7.040	6.708	8.656	4.008	4.478	8.101	7.856	9.213
GENIN	0.513	0.794	10.690	9.358	6.911	8.148	4.952	4.054	10.133	7.660	9.109
CYCGD	0.357	0.544	0.764	14.025	6.002	7.659	4.368	2.883	9.697	6.593	7.791
NCYCG	0.424	0.640	0.697	0.528	9.201	7.725	4.988	4.888	6.588	7.546	7.382
CYSER	0.424	0.779	0.774	0.635	0.791	10.362	4.869	5.005	7.761	8.658	8.461
NCYSR	0.355	0.331	0.432	0.332	0.469	0.431	12.314	5.755	4.942	5.150	5.398
UTILS	0.387	0.375	0.359	0.223	0.466	0.450	0.475	11.935	2.165	6.113	6.039
ITECH	0.343	0.558	0.737	0.615	0.516	0.573	0.335	0.149	17.706	6.991	8.421
FINAN	0.506	0.679	0.699	0.525	0.743	0.803	0.438	0.528	0.496	11.227	8.901
OTHER	0.467	0.655	0.683	0.510	0.597	0.645	0.377	0.429	0.491	0.652	16.620

Notes: This table reports estimates of the covariances and correlations between the returns on geographically diversified industry portfolios. Results are shown for four states: high global volatility, high industry volatility (Panel A); low global volatility, high industry volatility (Panel B); high global volatility, low industry volatility (Panel C); low global volatility, low industry volatility (Panel D). Numbers above the diagonal show covariance estimates, numbers on the diagonal show variance estimates, while numbers below the diagonal are estimates of the correlations.