DISCUSSION PAPER SERIES

No. 4368

COUNTRY AND INDUSTRY FACTORS IN STOCK RETURNS: A REGIME SWITCHING APPROACH

Luis Catão and Allan G Timmermann

FINANCIAL ECONOMICS

Centre for Economic Policy Research

www.cepr.org

Available online at: **www.cepr.org/pubs/dps/DP4368.asp**

ISSN 0265-8003

COUNTRY AND INDUSTRY FACTORS IN STOCK RETURNS: A REGIME SWITCHING APPROACH

Luis Catão, International Monetary Fund (IMF)
Allan G Timmermann, University of California, San Diego and CEPR

Discussion Paper No. 4368
April 2004

Centre for Economic Policy Research
90–98 Goswell Rd, London EC1V 7RR, UK
Tel: (44 20) 7878 2900, Fax: (44 20) 7878 2999
Email: cepr@cepr.org, Website: www.cepr.org

CEPR Discussion Paper No. 4368

April 2004

ABSTRACT

Country and Industry Factors in Stock Returns: A Regime Switching Approach*

An important question in international finance is to what extent stock return volatility is influenced by country location, industry affiliation, and global factors. This paper develops a new methodology to measure these effects, in which portfolios mimicking 'pure' country and industry factors are first constructed and their joint dynamics then modelled as regime-switching processes. Applying this methodology to a uniquely long set of international firm-level data, we identify well-defined high and low volatility states over the past 30 years, and show that the contribution of industry and country factors to stock return volatility varies markedly across such states. In particular, we find that the country factor contribution drops markedly when global equity market volatility rises, and that country return correlations become tighter when global and industry factors are both in a high volatility state. Key implications for global portfolio allocation are discussed.

JEL Classification: C10, G11 and G15
Keywords: diversification, international financial markets, risk and volatility states

Luis Catão
International Monetary Fund
700 19th Street NW
Washington DC 20431
USA
Email: lcatao@imf.org

Allan G Timmermann
UCSD Department of Economics
9500 Gilman Drive
La Jolla CA 92093-0508
USA
Tel: (1 858) 534 4860
Fax: (1 858) 534 7040
Email: atimmerm@weber.ucsd.edu

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=160775

For further Discussion Papers by this author see:
www.cepr.org/pubs/new-dps/dplist.asp?authorid=116464

*The views of this paper are the authors' alone and do not necessarily reflect those of the International Monetary Fund.

Submitted 08 March 2004

The rise in stock price volatility and the tighter co-movement across national markets in recent years have renewed interest in the issue of equity market volatility patterns and their sources. A central question is the extent to which a firm's stock returns are influenced by country-location, industry-affiliation, and global factors. If, for instance, stock returns are largely determined by country-specific factors such as national policies or institutions, then equity risk can be more effectively reduced by diversifying portfolios across national borders than by holding stocks of different industries in any one country. As such, risk diversification considerations will help boost international equity flows and favor the dissemination of "country funds" in asset management, carving on specialized knowledge of country specific characteristics shaping the return dynamics of individual stocks. Conversely, if industry-specific factors such as technology or product characteristics are main drivers of stock return variability, then risk diversification can be more effectively accomplished by holding equities of different industries in any given country, rather than by holding a single industry portfolio comprising firms from different countries. In this case, the risk diversification incentive to cross-border flows is weakened; and portfolio selection is, instead, likely to be more influenced by the dynamics of "industry funds" centered on industry specific knowledge guiding the choice of specific stocks.

In light of these practical ramifications, it is no surprise that a literature has sprung up trying to measure country- and industry-factor contributions to stock returns. The standard approach has consisted 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 common "global" factor representing the return of 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 (e.g. Heston and Rouwenhorst 1994; Beckers et al., 1996; Griffins and Karolyi, 1998; Serra, 2000), though it has been suggested that its importance has been waning in recent years, 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, alternatively, 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 have been argued to be significant drivers of stock return variability (Schwert, 1989; Eichengreen and Tong, 2003). Likewise, 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). This suggests the need for greater flexibility in modeling the dynamics of country and industry effects.

Against this background, the contribution of this paper is twofold. First, the paper advances a dynamically richer framework to gauge the contribution of country, industry, and global factors to variations in stock returns. Specifically, we propose 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 returns on the various country and industry portfolios are then modeled as regime-switching processes in a second stage. There are two obvious benefits of using cross-sectional regressions to form country and industry portfolios: 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 provide a richer characterization of the (possibly nonlinear) dynamics of common factors in portfolio returns.[1] The latter, in particular, has one key advantage over the methodologies used in previous studies: it captures the possibility that risk characteristics of the separate country, industry and global factors change at different frequencies by allowing shifts in these factors to be driven by separate state variables displaying different degrees of persistence. Allowing these three components to be in a different state at a given point in time reveals interesting time-variations in investors' diversification opportunities. This is because the correlation pattern between country and industry portfolios may (and do in fact) differ depending on whether the global factor is in a low or high volatility state, or whether the country and industry factors themselves are in a high or low volatility state.

The second contribution of the paper lies in applying this methodology to the data to highlight important features of the global stock market dynamics. To this end, we use a uniquely long dataset on firm-level stock returns which span 13 countries over 30 years, compared with at most 15 years or so of data in previous studies. Three main questions are then addressed. First, does the "stylized fact" that country factors dominate industry-affiliation effects hold uniformly or change only very slowly over time? Or, does it result from dynamic misspecification stemming from the use of the standard single-state linear model? Second, what is the typical "persistence" of such states (if there is in fact more than one), and what is the strength of the various individual country and industry return correlations within them? Third, how are these correlations between industry and country portfolios affected by variations in the global return component (which could be loosely viewed as a common "world" business cycle factor) and what are the respective implications for portfolio diversification?

The main results are as follows. First, we find very strong evidence of nonlinear dynamic dependencies in both industry and country returns. This clearly suggests that the dynamic "mixtures of normals" model underlying the Markov-switching approach is superior to the single state model in terms of modeling global stock returns. Second, we find that the country factor explains about 50 percent of market volatility over the entire 1973-2002 period, as opposed to 16 percent accounted for by the industry factor. This finding about the country factor prominence is obviously not new; but given the advantages of the proposed econometric methodology, we do see these estimates as better gauges of the benefits of cross-border risk diversification over the long term. Third, we find that these relative

contributions vary widely over time and across volatility states. In particular, the industry factor contribution to equity return volatility typically rises sharply during major industry shocks – such as the oil shocks of the 1970s and early 1980s and IT boom and bust more recently – which are, in turn, associated with higher industry-specific volatility and a marked drop in the country factor contribution. Comparing these results with those obtained by applying standard single-state models to the same data, we show that the definition of states as well as the respective factor contributions within them are more sharply identified with the proposed methodology, and we discuss why this should be expected.

The fourth and main set of new empirical results pertains to the pattern of cross-country portfolio correlations during high and low global volatility states. As mentioned above, the proposed methodology is well suited to address this question and we show that when both the global and industry factors are in the high volatility state (as in the post-1997 period), average correlations between country portfolios become tighter than average correlations across industry portfolios. One key implication of our results on this count is that, even though high industry volatility states are estimated to be much less persistent than low volatility ones, the sharp rise in country portfolio correlations during high global volatility states undermines the benefits of cross-border diversification strategies during those periods. This, in turn, highlights a potentially important connection between global stock market volatility and the expected pattern of international equity flows, which we briefly discuss at the end.

The remainder of the paper is structured as follows. Section I lays out the econometric methodology, while section II discusses the data. The empirical characterization of the single and joint dynamics of country and industry portfolios and of the global factor is provided in section III. Section IV presents variance decomposition results on the relative contribution of each factor to overall stock return volatility. Section V examines the within-state portfolio correlations and examines the respective implications for global risk diversification. Section VI concludes.

I. ECONOMETRIC METHODOLOGY

Our panel of individual stock returns is 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. To deal with this problem, we present an approach that does not entail loosing 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:

$$R_{ijkt} = \alpha_t + \beta_{jt} + \gamma_{kt} + \varepsilon_{it}, \tag{1}$$

where R_{ijkt} stands for the return at time t of the ith firm in the jth industry and the kth 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:

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

Here $e_{ij\beta}$ is a dummy variable defined as 1 for the ith firm's industry and zero otherwise, while $e_{ik\gamma}$ is a dummy defined as 1 for the ith 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, since 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: $\sum_{j=1}^{J}\beta_j \sum_{i=i}^{N} e_{ij\beta}x_i = \sum_{j=1}^{J}\beta_j w_j = 0$, $\sum_{k=1}^{K}\gamma_k \sum_{i=1}^{N} e_{ij\gamma}x_i = \sum_{k=1}^{K}\gamma_k v_k = 0$, where N is the total number of firms in a given period and w_j is 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. So, the industry and country effects are estimated as deviations from the intercept α. Subject to these zero sum restrictions, equation (2) can be estimated using weighted least squares, with each stock return being 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).

The weighted least squares estimates of the parameters in (2) yield 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 in each cross-section can vary and yet a balanced panel of portfolios of country and industry specific excess returns can be formed. This effectively summarizes the relevant information from the original unbalanced panel.

We can re-write (2) more succinctly by defining the excess return vectors as:

$$\boldsymbol{\beta}_t = \begin{pmatrix} \beta_{1t} \\ \beta_{2t} \\ \vdots \\ \beta_{Jt} \end{pmatrix}, \qquad \boldsymbol{\gamma}_t = \begin{pmatrix} \gamma_{1t} \\ \gamma_{2t} \\ \vdots \\ \gamma_{Kt} \end{pmatrix},$$

so that:

$$R_{ijkt} = \alpha_t + \mathbf{e}'_{i\beta}\boldsymbol{\beta}_t + \mathbf{e}'_{i\gamma}\boldsymbol{\gamma}_t + \varepsilon_{it}. \tag{3}$$

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 a $K \times 1$ 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 ($\boldsymbol{\beta}_t$) and country components ($\boldsymbol{\gamma}_t$) 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), and Hamilton (1988) find evidence of multiple states in the dynamics of interest rates, while Ang and Bekaert (2001), 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)).

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

$$\begin{aligned} \alpha_t &= \mu_{\alpha s_{\alpha t}} + \sigma_{\alpha s_{\alpha t}} \varepsilon_{\alpha t}, \\ \beta_{jt} &= \mu_{\beta_j s_{\beta j t}} + \sigma_{\beta_j s_{\beta j t}} \varepsilon_{\beta j t}, \\ \gamma_{kt} &= \mu_{\gamma_k s_{\gamma k t}} + \sigma_{\gamma_k s_{\gamma k t}} \varepsilon_{\gamma k t}. \end{aligned} \tag{4}$$

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 $\mu_{\beta j1}$ or $\mu_{\beta j2}$ while its volatility is either $\sigma_{\beta j1}$ or $\sigma_{\beta j2}$.

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:

$$\begin{aligned} &\Pr(S_{\alpha t} = s_\alpha \mid S_{\alpha t-1} = s_\alpha) = p_{\alpha s_\alpha s_\alpha}, \\ &\Pr(S_{\beta jt} = s_{\beta_j} \mid S_{\beta_j t-1} = s_{\beta j}) = p_{\beta j s_{\beta j} s_{\beta j}}, \\ &\Pr(S_{\gamma kt} = s_{\gamma k} \mid S_{\gamma kt-1} = s_{\gamma k}) = p_{\gamma k s_{\gamma k} s_{\gamma k}}. \end{aligned} \tag{5}$$

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., $\pi_{s\alpha t} = \Pr(S_{\alpha t} = s_\alpha \mid \Gamma_t)$, $\pi_{s\beta_j t} = \Pr(S_{\beta_j t} = s_{\beta_j} \mid \Gamma_t)$, $\pi_{s\gamma_k t} = \Pr(S_{\gamma_k t} = s_\gamma \mid \Gamma_t)$, 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. This implies that the return process will be a mixture of normal random variables, the resulting distribution of which is capable of accommodating features such as skews and fat tails that are frequently found in financial data.

Under this model, the return on the *i*th company in industry *j* and country *k* is affected by separate global, industry and country regimes plus an idiosyncratic error term

$$R_{ijkt} = \mu_{\alpha s_{\alpha t}} + \mu_{\beta_j s_{\beta jt}} + \mu_{\gamma_k s_{\gamma kt}} + \sigma_{\alpha s_{\alpha t}} \varepsilon_{\alpha t} + \sigma_{\beta_j s_{\beta jt}} \varepsilon_{\beta jt} + \sigma_{\gamma_k s_{\gamma kt}} \varepsilon_{\gamma kt} + \varepsilon_{it}. \tag{6}$$

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, one can think of a number of common shocks of political and institutional origins that spread mainly along country lines as opposed to industry lines.

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:

$$\begin{aligned} \alpha_t &= \mu_{\alpha s_{\alpha t}} + \varepsilon_{\alpha s_{\alpha t}}, \\ \boldsymbol{\beta}_t &= \boldsymbol{\mu}_{\beta s_{\beta t}} + \varepsilon_{\beta s_{\beta t}}, \\ \boldsymbol{\gamma}_t &= \boldsymbol{\mu}_{\gamma s_{\gamma t}} + \varepsilon_{\gamma s_{\gamma t}}, \end{aligned} \tag{7}$$

where $\mu_{\alpha s_{\alpha t}}$ is the scalar global mean return in state $s_{\alpha t}$, $\boldsymbol{\mu}_{\beta s_{\beta t}}$ is a J-vector of industry means in state $s_{\beta t}$, $\boldsymbol{\mu}_{\gamma s_{\gamma t}}$ is a K-vector of country means in state $s_{\gamma t}$. Furthermore, the innovations to returns are Gaussian with zero mean and state-specific variances $\varepsilon_{\alpha s_{\alpha t}} \sim \left(0, \sigma^2_{\alpha s_{\alpha t}}\right)$ $\varepsilon_{\beta s_{\beta t}} \sim \left(0, \Omega_{\beta s_{\beta t}}\right)$, $\varepsilon_{\gamma s_{\gamma t}} \sim \left(0, \Omega_{\gamma s_{\gamma t}}\right)$, where $\sigma^2_{\alpha s_{\alpha t}}$ is the scalar variance of global return in state $s_{\alpha t}$, $\Omega_{\beta s_{\beta t}}$ is the *JxJ* variance-covariance matrix of industry returns in state $s_{\beta t}$, $\Omega_{\gamma s_{\gamma t}}$ is the *KxK* 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:

$$\begin{aligned} \Pr(S_{\alpha t} = s_\alpha \mid S_{\alpha t-1} = s_\alpha) &= p_{\alpha s_\alpha s_\alpha}, \\ \Pr(S_{\beta t} = s_\beta \mid S_{\beta t-1} = s_\beta) &= p_{\beta s_\beta s_\beta}, \\ \Pr(S_{\gamma t} = s_\gamma \mid S_{\gamma t-1} = s_\gamma) &= p_{\gamma s_\gamma s_\gamma}. \end{aligned} \tag{8}$$

The regime switching model is fully specified by the state transitions (8), the return equations (3) and (7) 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 (see Hamilton, 1994, for details).

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. 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 other than indirectly as the parameter estimates get updated over time.

Regime switching models can capture very rich dynamics in our model: while the mean and variance of returns are constant within each state, as the state probabilities vary over time, the conditional correlation, mean and variances of returns are allowed to change over time. Since the true state probabilities are unobserved, investors have to use updated (*ex ante* or filtered) state probabilities. These can change either gradually (if the filtered state probabilities change slowly) or rapidly (if filtered state probabilities move more suddenly). Using the ex-ante state probabilities, this means that both gradual and more sudden time-variations in expected returns and risk can be accommodated by the model.

II. 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.[2] 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, they span a shorter period and the estimation of the econometric model for a significantly larger number of countries becomes unfeasible due to degrees of freedom limitations. This bodes well with the conclusion of recent work that includes both mature and emerging markets in (value weighted) regressions for the post-1985 period and found that trends in the relative contribution of country and industry factors are basically the same regardless of whether one includes or excludes the emerging market sub-sample (Brooks and Catão, 2000; Brooks and Negro, 2002).

Firms in these 13 countries are then 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. While some recent papers argue in favor of a finer industry classification, 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) from "old economy" industries.[3]

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. While this bias no doubt affects average rates of return, it does not seem to be too consequential for the analysis of relative factor contributions to market volatility, which is this paper's central concern. This can be gauged from a comparison between our data and the data compiled by one recent study which attempts to correct for this survivorship bias using the Datastream list of dead stocks to correct for this bias in the post-1986 period, when such a list is available.[4] The second deficiency in the data is that of including only post-merger companies, dropping companies that go into the merger. The most likely effect of this is to bias the estimates in favor of finding more pronounced global industry effects in the 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 above. This is a crucial advantage required for precise estimation of regime switching processes. 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 econometric results arising from the deficiencies mentioned above

III. Global Stock Return Dynamics

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.[5] 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.[6] This is of course the type of situation where mixtures of normals may be better able to capture the underlying return distribution.

A. Nonlinearity in Returns

Previous studies of country—and industry effects 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) which, unlike standard likelihood ratio tests, has the advantage of taking into account for the problem associated with unidentified nuisance parameters under the null hypothesis of a single regime. 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 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 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.[7]

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. Individual Portfolio Dynamics

Panel A of Table 4 shows 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 duration of the two states (columns 7 and 8).

Differences between the volatility parameters of the two regimes are highly significant, both economically and statistically.[8] 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 bar one country, Japan, the high volatility state has the lowest persistence. This is consistent with the well-established notion that bursts of volatility do not last all that long. In some countries such as Belgium the duration of the high volatility state is very short. On average, the duration of the high volatility state is 16 months while that of the low volatility state is 39 months. As a consequence, the steady-state probabilities indicate that 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.

Turning to the industry 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 and 2.1 percent per month in the high and low volatility states, respectively. As with the country portfolios, the 'stayer' probability is higher in the low volatility state than in the high volatility state, but both states are highly persistent with average stayer probabilities of 91 and 94 percent, respectively. Again, the average duration of the low volatility state is more than twice as long as that of the high volatility state.

C. Joint Portfolio Dynamics

Much of the extant literature seeks to answer how much country and industry effects matter "on average". The results above have identified important differences in regimes. Yet, while the above results have been deriving under the assumption of dynamics that are specific to each industry or country portfolio, 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 that allows for separate regimes in the joint country and in the joint industry portfolio returns. This yields a nonlinear dynamic common factor specification of the type discussed in section II, which is clearly distinct from the vast majority of recent work on dynamic factor models (cf. Stock and Watson, 1998) in that it does not impose a linear factor structure. This distinction is particularly important when the main interest lies in extracting common factors in the volatility of returns on various portfolios, given overwhelming empirical evidence of time-varying volatilities in stock returns.

We estimate the proposed joint regime switching model 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. The joint estimation of the parameters of a highly nonlinear model for such a large system is a nontrivial exercise. Yet, it can yield important insights into the joint dynamics of portfolio returns, as will be discussed below.

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.[9] As expected, the null hypothesis of a linear model with a single state is strongly rejected for the country, industry, and world models. All three information criteria support 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 support the two-state specification over the one-state model for the global return model. Table 5 also shows that the two states identified in country returns have persistence parameters of 0.975 and 0.976, implying that the durations of the two states are high at 40 and 42 months, respectively. Clearly the 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 on average.

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).

Figure 1 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. The common industry regime identifies four high volatility periods around the oil shocks of the early seventies (1974) and 1979-80, a spell from 1986 to September 1987 followed by the more recent period from late 1997. The global return component follows shorter, cyclical movements that nevertheless are well identified by the model. This model thus identifies more regime shifts than the models fitted to the common country and industry portfolios.

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.

IV. Variance Decompositions

A central question in the literature on country and industry effects on stock returns is the 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 market 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:

$$\begin{aligned}\sigma_t^2 = &\sum_{s_{\alpha t}} \pi_{s_{\alpha t}} (\sigma_{s_{\alpha t}}^2 + (\mu_{\alpha s_{\alpha t}} - \bar{\mu}_{\alpha t})^2) \\ &+ \sum_{s_{\beta_t}} \pi_{s_{\beta t}} (\boldsymbol{\omega}_{\beta t}' \boldsymbol{\Omega}_{\beta s_{\beta t}} \boldsymbol{\omega}_{\beta t} + \boldsymbol{\omega}_{\beta t}' (\boldsymbol{\mu}_{\beta s_{\beta t}} - \bar{\boldsymbol{\mu}}_{\beta t})^2) \\ &+ \sum_{s_{\gamma t}} \pi_{s_{\gamma t}} (\boldsymbol{\omega}_{\gamma t}' \boldsymbol{\Omega}_{\gamma s_{\gamma t}} \boldsymbol{\omega}_{\gamma t} + \boldsymbol{\omega}_{\gamma t}' (\boldsymbol{\mu}_{\gamma s_{\gamma t}} - \bar{\boldsymbol{\mu}}_{\gamma t})^2),\end{aligned} \tag{9}$$

where $\boldsymbol{\omega}_{\beta t}$ is the vector of weights for the industry portfolios and $\boldsymbol{\omega}_{\gamma t}$ is the vector of weights of country portfolios. $\bar{\boldsymbol{\mu}}_{\alpha t} = \sum_{s_{\alpha t}} \pi_{s_{\alpha t}} \boldsymbol{\mu}_{\alpha s_{\alpha t}}$ is the conditional expectations of the global portfolio returns, $\bar{\boldsymbol{\mu}}_{\beta t} = \sum_{s_{\beta t}} \pi_{s_{\beta t}} \boldsymbol{\mu}_{\beta s_{\beta t}}$ and $\bar{\boldsymbol{\mu}}_{\gamma t} = \sum_{s_{\gamma t}} \pi_{s_{\gamma t}} \boldsymbol{\mu}_{\gamma s_{\gamma t}}$ are Jx1 and Kx1 vectors of conditionally expected returns on the industry and country portfolios, respectively. The first component in (9) 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 market variance changes over time due to time-variations in the state probabilities.[10]

Figure 2 plots the time-series of the market volatility component computed from (9). 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 market 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 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.[11]

The measure of market variance in (9) readily lends itself to a decomposition into its three constituents. Figure 3 shows the fraction of total market variance represented by the average country, 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 noticeably

lower in periods such as the 1974-75 oil shock, the 1987 stock market crash and the information technology boom of the late 1990's.

Likewise, the fraction of total market volatility due to the industry component also varies considerably as shown in the middle panel of Figure 3. 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.[12] Figure 3 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 to 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 3, this is 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.

It is instructive to compare these results with those obtained through the widespread practice of estimating relative contributions by the time-series variances of the estimated β_{jt} and γ_{kt}, computed over a rolling window. We follow the common practice of using a window length of 3 years, but also experimented with 4- and 5-year rolling windows and found the trends to be very similar. To facilitate comparison with our results, Figure 4 plots the 3-year rolling window results together with our regime switching estimates previously plotted in Figure 3. Clearly, the rolling window approach smoothes out the shifts in factor volatilities and their relative contributions. The respective states become less clearly defined and the approach overlooks the important spikes associated with the oil shocks of 1973-74 and 1979-80.

Finally, we also consider an alternative and complementary measure of the relative significance of the industry and country contributions to portfolio returns, which was proposed by Griffin and Karolyi (1998) and replicated by others (Baca et al., 2000). Our two-stage econometric methodology allows us to extend the Griffin and Karolyi decomposition scheme 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., $\sum_{j=1}^{J} \omega_{jkt}^{\beta} \hat{\beta}_{jt}$) plus a "pure" country effect $\hat{\gamma}_{kt}$:[13]

$$R_{kt} - \hat{\alpha}_t = \sum_{j=1}^{J} \omega_{jkt}^{\beta} \hat{\beta}_{jt} + \hat{\gamma}_{kt}, \tag{10}$$

where ω_{jkt}^{β} is the jth 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

$$Var(R_{kt} - \hat{\alpha}_t \mid s_{\beta t}, s_{\gamma t}) = (\boldsymbol{\omega}_{kt}^{\beta})'\boldsymbol{\Omega}_{\beta_{s_\beta}}\boldsymbol{\omega}_{kt}^{\beta} + \mathbf{e}_k^{'}\boldsymbol{\Omega}_{\gamma s_\gamma}\mathbf{e}_k + 2(\boldsymbol{\omega}_{kt}^{\beta})'Cov(\beta_{jt}, \gamma_{kt} \mid s_{\beta t}, s_{yt}), \qquad (11)$$

where $\boldsymbol{\omega}_{kt}^{\beta}$ 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, $\hat{\beta}_{jt}$:

$$R_{jt} - \hat{\alpha}_t = \sum_{k=1}^{K} \omega_{jkt}^{\gamma}\hat{\gamma}_{kt} + \hat{\beta}_{jt}, \qquad (12)$$

where ω_{jkt}^{γ} is the kth 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

$$Var(R_{jt} - \hat{\alpha}_t \mid s_{\beta t}, s_{\gamma t}) = (\boldsymbol{\omega}_{jt}^{\gamma})'\boldsymbol{\Omega}_{\gamma_{s_\gamma}}\boldsymbol{\omega}_{jt}^{\gamma} + \mathbf{e}_j^{'}\boldsymbol{\Omega}_{\beta s_\beta}\mathbf{e}_j(\boldsymbol{\omega}_{jt}^{\gamma})' + 2Cov(\beta_{jt}, \gamma_{kt} \mid s_{\beta t}, s_{yt}), \qquad (13)$$

where $\boldsymbol{\omega}_{kt}^{\gamma}$ is the K-vector of market capitalization weights of the countries in industry j.

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 (11) and (13) 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 results therefore suggest that decomposition results reported in the existing literature vary considerably over economic states.

V. Implications for Global Risk Diversification

The above decompositions of market 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 which in turn tends to raise the equity premium and drive up the cost of capital.

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 Wadhwani, 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 Wadhwani (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. An important spin-off of the proposed approach that, to be best of our knowledge, has been unexplored in the literature, is the possibility that the country and industry portfolios may be in different states at a given point in time, thus raising interesting possibilities for risk diversification.

To see this, recall that 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 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 $Cov(\alpha_t, \gamma_{kt} \mid s_t, s_{\gamma t})$ can be consistently estimated as follows:

$$
\begin{aligned}
Cov(\alpha_t, \beta_{jt} \mid s_{\alpha t}, s_{\beta t}) &= \frac{\sum_{t=1}^{T} \pi_{s_{\alpha t}} \pi_{s\beta t} (\alpha_t - \hat{\alpha}_{s_{\alpha t}})(\beta_{jt} - \hat{\beta}_{js_{\beta t}})}{\sum_{t=1}^{T} \pi_{s_{\alpha t}} \pi_{s_{\beta t}}}, \\
Cov(\alpha_t, \gamma_{kt} \mid s_{\alpha t}, s_{\gamma t}) &= \frac{\sum_{t=1}^{T} \pi_{s_{\alpha t}} \pi_{s\gamma k} (\alpha_t - \hat{\alpha}_{s_{\alpha t}})(\gamma_{kt} - \hat{\gamma}_{ks_{\gamma t}})}{\sum_{t=1}^{T} \pi_{s_{\alpha t}} \pi_{s\gamma t}}, \\
Cov(\beta_t, \gamma_t \mid s_{\beta t}, s_{\gamma t}) &= \frac{\sum_{t=1}^{T} \pi_{s_{\beta t}} \pi_{s_{\gamma t}} (\beta_{jt} - \hat{\beta}_{js_{\beta t}})(\gamma_{kt} - \hat{\gamma}_{ks_{\gamma t}})}{\sum_{t=1}^{T} \pi_{s_{\beta t}} \pi_{s\gamma t}}.
\end{aligned}
\tag{14}
$$

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 are below.

For the country portfolios, the key findings are as follows. 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.[14] 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 distinct econometric methodologies and data series 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 13 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 menu of possible combinations 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. 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.

Important practical implications follow from these results. Generally, it will be more difficult to minimize equity risk through cross-border diversification when the global volatility process is in the high volatility state. On a macro level, this suggests that

international capital flows should be expected to rise or accelerate during periods of low global stock market volatility and to web during high volatility states. Moreover, as the gains to cross-border diversification appear to be especially meager when global and industry factors *both* simultaneously lie in a high volatility state, this suggests that cross-border risk diversification should not be so beneficial those sub-periods, thus likely dampening international equity flows. This raises the question of whether these patterns are actually observed in the data. While a systematic testing of this relationship is no mean task – not only because international capital flows are driven by a number of effects at play (see, e.g. Tesar and Werner, 1994; Bekaert, Harvey, and Lumsdaine, 2002), but also because of considerable data problems, even if one were to limit the analysis to US data (see Warnock and Cleaver, 2003) – it clearly warrants further research.

VI. CONCLUSION

The extent to which firms' stock returns are influenced by country-location, industry-affiliation, and global factors is a key question in international finance. So it is clearly important to have a sound empirical methodology to measure these effects which allows for rich dynamics typically observed in financial data. This paper has presented a new two-stage methodology in which loss of information is minimized via the construction of industry and country portfolios from unbalanced firm level data in a first stage, with their joint dynamics modeled as regime-switching processes in a second stage. The model has been estimated using a new global firm-level dataset spanning over three decades, yielding a number of interesting and important findings.

First, for most countries and industries, there is very strong evidence of two "regimes" or "states" characterized by very different levels of volatility. Both regimes tend to be highly persistent, with high volatility states proving to be the least persistent. On average, our estimates for individual country and individual industry portfolios show that high volatility states last less than half of that of high volatility states. This inverse relationship between stock return volatility and persistence across states for the various countries studied is consistent with the findings of Ang and Bekaert (2002) and Perez-Quiros and Timmermann (2000) looking at other financial indicator over a more limited geographical universe and distinct time span.

Second, we find 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 sharp oil price changes of the 1970s/early 1980s and the IT boom and bust more recently. Having identified such common country and industry factors, the proposed methodology has permitted the estimation of the respective factor contribution to market volatility over the entire 30-year period as well as within states, in a way that is consequently bound to be far more precise than that of the

linear single-state model of previous studies. Over 1973–2002 as a whole, we find that the country factor contribution averaged some 50 percent as opposed to 16 percent for the industry factor —a figure that justifies the traditional emphasis on the importance of country as compared with industry diversification strategies over the long term.

Yet, as an important qualification to the latter result, the paper shows that there have been important variations across volatility states, many of which have been overlooked in previous studies. Moreover, such inter-state variations are shown to have important implications for global risk diversification. Since each factor in the model is allowed to be in one of two states at any point in time, eight possible state combinations arise, with each combination possibly giving rise to a stronger or weaker pattern of correlations between the various portfolios. 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 doubled in the high volatility state on average. It follows that the benefits of investing abroad tend to be considerably smaller when global volatility is high. Furthermore, pair-wise correlations between the various country portfolios indicate that such benefits are even smaller when international diversification is confined to certain subset of countries, such as the Anglo-Saxon nations or within continental Europe—a finding consistent with the recent literature taking a "geography view" of financial markets (e.g., Portes and Rey (2001)). Conversely, international diversification is far more beneficial when global volatility is low, and especially so when the low volatility of the global factor is juxtaposed to a low volatility state in the common industry factor.

These findings have important implications for risk management and patterns of cross-border equity flows, some of them clearly warranting further research. This is notably the case of the aforementioned evidence on country portfolio correlations across high and low global volatility states, which points to a potentially important link between global equity return volatility states and expected swings in cross-border flows. If this relationship in fact holds, it may help explain, for instance, the massive wave of cross-border equity flows during global low volatility states such as during 1992-1997:6, as well as its subsequent reversal during the post-1997 high volatility state, but clearly further research considering a variety of other factors is in order before any robust inference can be made. More generally, this paper's findings suggest that portfolio allocation strategies should reap significant benefits from careful monitoring of the underlying state probabilities and of the estimated cross-country and cross-industry portfolio correlations within states. This monitoring should prove especially valuable in light of the finding that state probabilities tend to be highly persistent, thereby implying considerable predictability of future states once the current one has been estimated with reasonable precision.

References

Ang, Andrew and Geert Bekaert, 2002, "International Asset Allocation with Regime Shifts," *Review of Financial Studies*, 15, 1137-87.

_____, 2002, "Regime Switches in Interest Rates," *Journal of Business and Economic Statistics*, Vol. 20, pp. 163–182.

Baca, S.P., B. Garbe, and R.A. Weiss, 2000, "The Rise of Industry Effects in Major Equity Markets," *Financial Analysts Journal*, September/October, pp. 35–40.

Bekaert, Geert and Campbell R. Harvey, 1997, "Emerging Equity Market Volatility," *Journal of Financial Economics,* Vol. 43, pp.29-77.

_____, 2002, "The Dynamics of Emerging Market Equity Flows,", *Journal of International Money and Finance,* Vol. 21, pp.295-350.

_____, and Angela Ng, 2003, "Market Integration and Contagion," *Journal of Business*, forthcoming.

Beckers, Stan, G. Connor, and R. Curds, 1996, "National versus Global Influences on Equity Returns." *Financial Analysts Journal*, March/April, pp. 31–39.

Beckers, Stan, R. Grinold, A. Rudd, and D. Stefek, 1992, "The Relative Importance of Common Factors Across the European Equity Markets," *Journal of Banking and Finance*, Vol. 16, pp. 75–95.

Brooks, Robin and Luis Catão, 2000, "The New Economy and Global Stock Returns", IMF working paper 00/216, Washington: International Monetary Fund.

Cavaglia, Stefano, C. Brightman, and M. Aked, 2000, "The Increasing Importance of Industry Factors", *Financial Analysts Journal*, September/October, pp. 41–54.

Davies, R., 1977, "Hypothesis Testing When a Nuisance Parameter is Present Only Under the Alternative," *Biometrica*, Vol. 64, pp. 247–254.

Driffill, John and Martin Sola, 1994, "Testing the Term Structure of Interest Rates from a Stationary Switching Regime VAR," *Journal of Economic Dynamics and Control* Vol. 18, pp. 601–628.

Eichengreen, Barry and Hui Tong, 2003, "Stock Market Volatility and Monetary Policy: What the Historical Record Shows," unpublished manuscript, University of California, Berkeley.

Fama, Eugene, and J. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests", *Journal of Political Economy*, Vol. 71, pp.607-636.

Gray, Stephen, 1996, "Modeling the Conditional Distribution of Interest Rates as Regime-Switching Process," *Journal of Financial Economics* Vol. 42, pp. 27–62.

Griffin, John and G. Andrew Karolyi, 1998, "Another Look at The Role of Industrial Structure of Markets for International Diversification Strategies," *Journal of Financial Economics* Vol. 50, pp. 351–373

Hamilton, James, 1988, "Rational Expectations Econometric Analysis of Changes in Regime: An Investigation of the Term Structure of Interest Rates," *Journal of Economic Dynamics and Control,* Vol. 12, pp. 365–423.

———, 1989, "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," *Econometrica*, Vol. 57, pp. 357–384.

———, 1994, *Time Series Analysis*, Princeton.

Heston, Steven L. and K. Geert Rouwenhorst, 1994, "Does Industrial Structure Explain the Benefits of International Diversification," *Journal of Financial Economics*, Vol. 36, pp. 3–27.

International Monetary Fund, 2000, "*World Economic Outlook – Asset Prices and the Business Cycle*," Washington D.C.: International Monetary Fund.

Karolyi, Andrew and René Stultz, 1996, "Why do Markets Move Together? An Investigation of U.S.-Japan Stock Return Comovements", *Journal of Finance,* Vol. 51, pp. 951–86.

King, Mervin, Enrique Sentana, and Sushil Wadhwani, 1994, "Volatility and Links Between National Stock Markets," *Econometrica,* Vol. 62, pp. 901–33.

Lin, Weng-Ling, Robert F. Engle, and Ito Takatoshi, 1994, "Do Bull and Bears Move Across Broders? Transmission of International Stock Returns and Volatility," *Review of Financial Studies,* Vol. 7, pp. 507–538.

Longin, François and Bruno Solnik, 1995, "Is the Correlation in International Equity Returns Constant: 1970-1990," *Journal of International Money and Financ*e, Vol. 14, pp. 3–26.

———, 2001, "Extreme Correlation of International Equity Markets," *Journal of Finance*, Vol. 56, pp. 649–76.

Pagan, Adrian and G.William Schwert, 1990, "Alternative Models for Conditional Stock Volatility," *Journal of Econometrics*, Vol. 92, pp. 307–28.

Perez-Quiros, G. and A. Timmermann, 2000, "Firm Size and Cyclical Variations in Stock Returns," *Journal of Finance 55*, pp. 1229–62.

Portes, R. and Helène Rey, 2001, "The Determinants of Cross-Border Equity Flows: The Geography of Information," NBER working paper 7336.

Schwert, William, G., 1989, "Why Does Stock Market Volatility Change Over Time?", *Journal of Finance* 44, pp. 1115–1153.

Serra, Ana P., 2000, "Country and Industry Factors in Returns: Evidence from Emerging Markets' Stocks," *Emerging Markets Review*, Vol. 1, pp. 127–151.

Solnik, Bruno, C. Broucrelle and Y. Le Fur, 1996, "International Market Correlation and Volatility," *Financial Analysts Journal*, September-October, pp. 17–34.

_____ and Jacques Roulet, 2000, "Dispersion as Cross-Sectional Correlation," *Financial Analysts Journal*, Vol. 56, No 1, pp. 54–61.

Stock, James and Mark Watson, 1998, "Diffusion Indexes," NBER working paper 6702, Cambridge, Mass.: National Bureau of Economic Research.

Tesar, L. and Werner, I, 1994, "International Equity Transactions and U.S. Portfolio Choice," in Frankel, J. (ed.), *The Internationalization of Equity Markets*, Chicago.

Timmermann, Allan, 2000, "Moments of Markov Switching Models," *Journal of Econometrics,*Vol. 96, pp. 75–111.

Turner, Christopher, Richard Startz, and Charles Nelson, 1989, "A Markov Model of Heteroskedasticity, Risk and Learning in the Stock Market," *Journal of Financial Economics*, Vol. 25, pp. 3–22.

Whitelaw, Robert F., 2001, "Stock Market Risk and Return: An Equilibrium Approach," *Review of Financial Studies,* Vol. 13, pp. 521–48.

Notes to Main Text:

[1] See Timmermann (2000) and Perez-Quiros and Timmermann (2001) for a detailed discussion of this point.

[2] 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 (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, entailing too short time series for the estimation of Markov-switching processes.

[3] While Griffin and Karolyi (1998) note that a finer industry disaggregation may yield a more accurate measure of industry effects, their main result – the far greater dominance of country-specific effects—hardly changes with the move to a finer industry breakdown.

[4] In their estimates, Brooks and Negro (2002) obtain the following figures for the capitalization-weighted time-series variance of country effects (also gauged by the same parameter γ_{kt} in the Heston-Rouwenhorst decomposition scheme): 18.47 over 1986:3 to 1990:2; 21.08 over 1990:3 to 1994:2; and 9.12 between 1994:3 and 1998:2. Using the same 4-year fixed windows and a similar group of mature markets but without including dead stocks, our respective estimates are 19.21, 22.10, and 8.80. So, the differences are small and have no discernable effect on trends.

[5] 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.

[6] Results of the Jarque-Bera test statistics are available from the authors upon request.

[7] 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.

[8] 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.

[9] 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.

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

[11] Using, however, *aggregate* stock price data spanning over a century for advanced countries, Eichengreen and Tong (2003) suggest that stock market volatility displays a U-shape in most countries. It remains to be established the extent to which this result stems from their use of much longer data series or from their methodology, based on rolling standard deviations of stock price changes and univariate Garch(1,1) regressions with deterministic trends.

[12] 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.

[13] 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.

[14] 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.

Figure 1. Smoothed State Probabilities for Common Components
(High Volatility State)

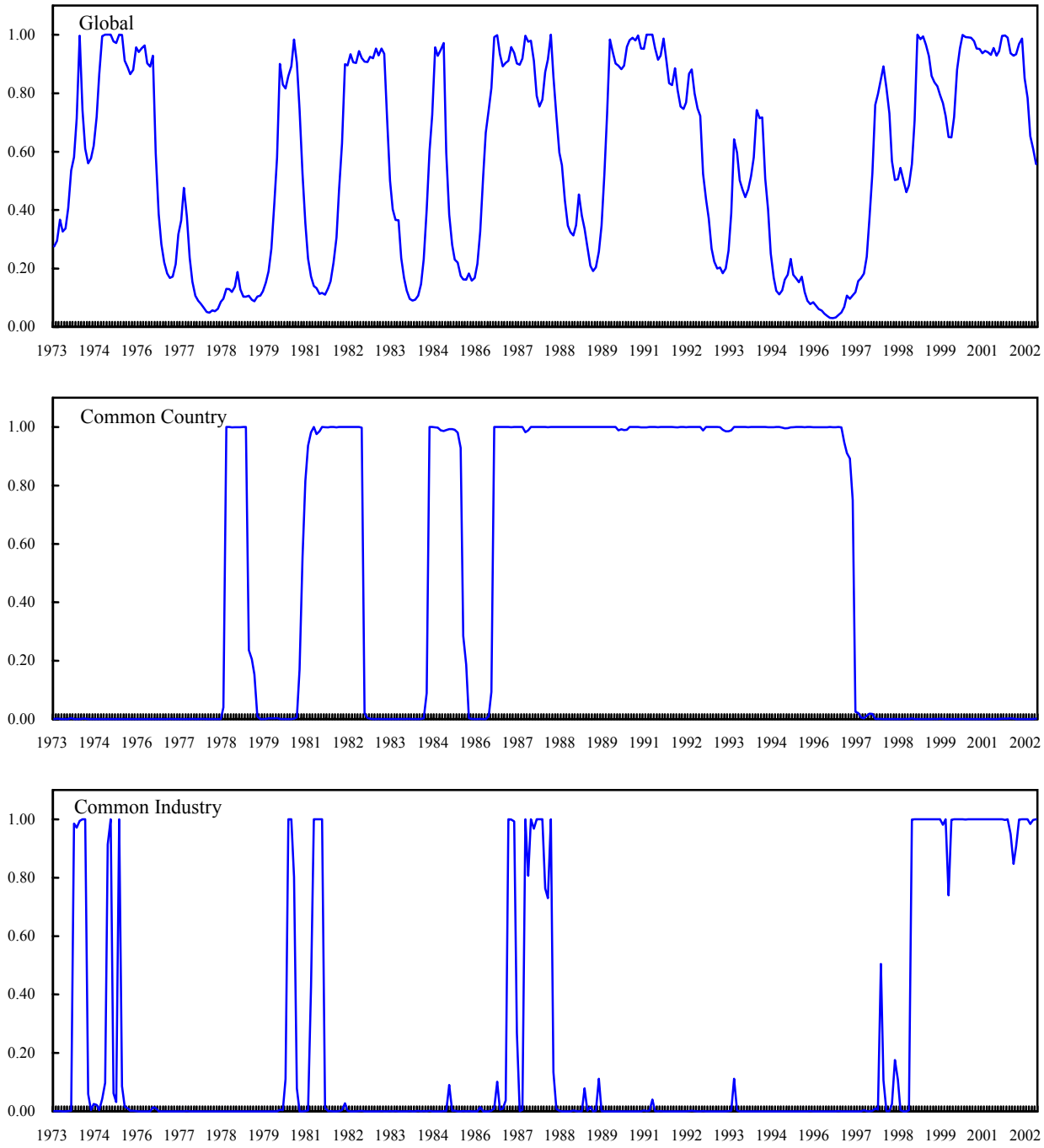

Figure 2. Market Volatility

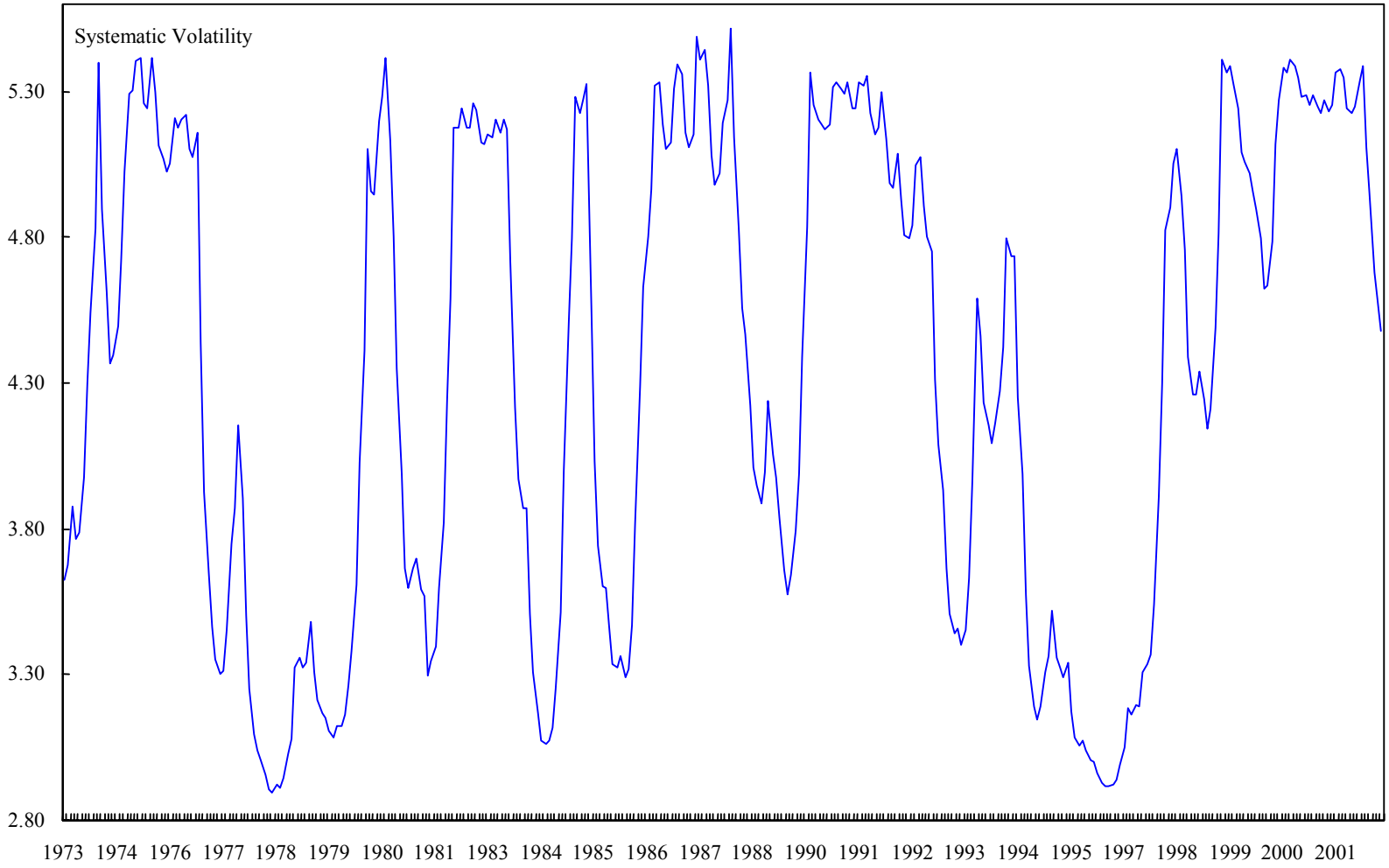

Figure 3. Decomposition of Systematic Variance into Country, Industry and Global Factors

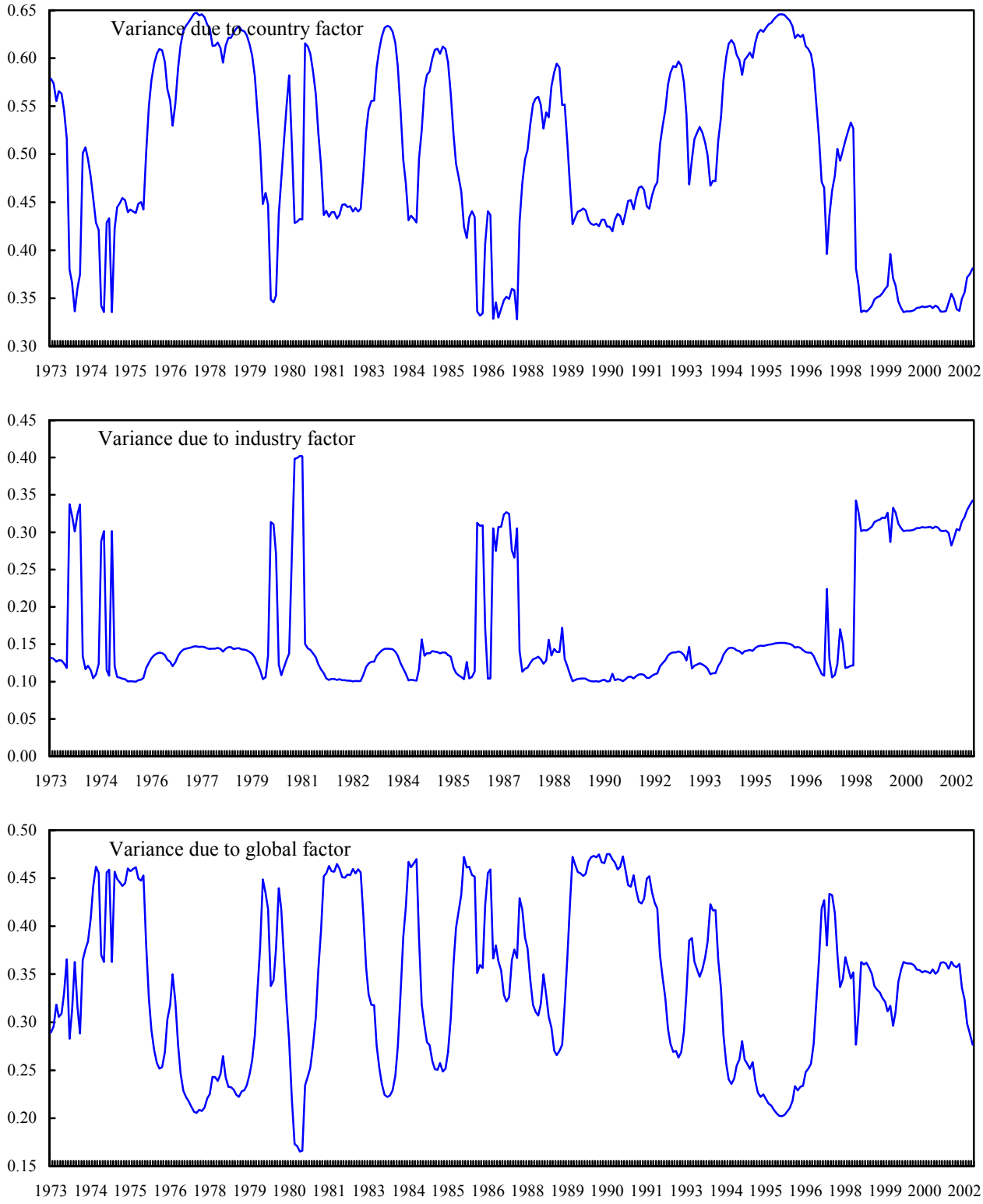

Figure 4. Comparison of Variance Decomposition Results between the Proposed Model and the 36-Month Rolling Window Approach

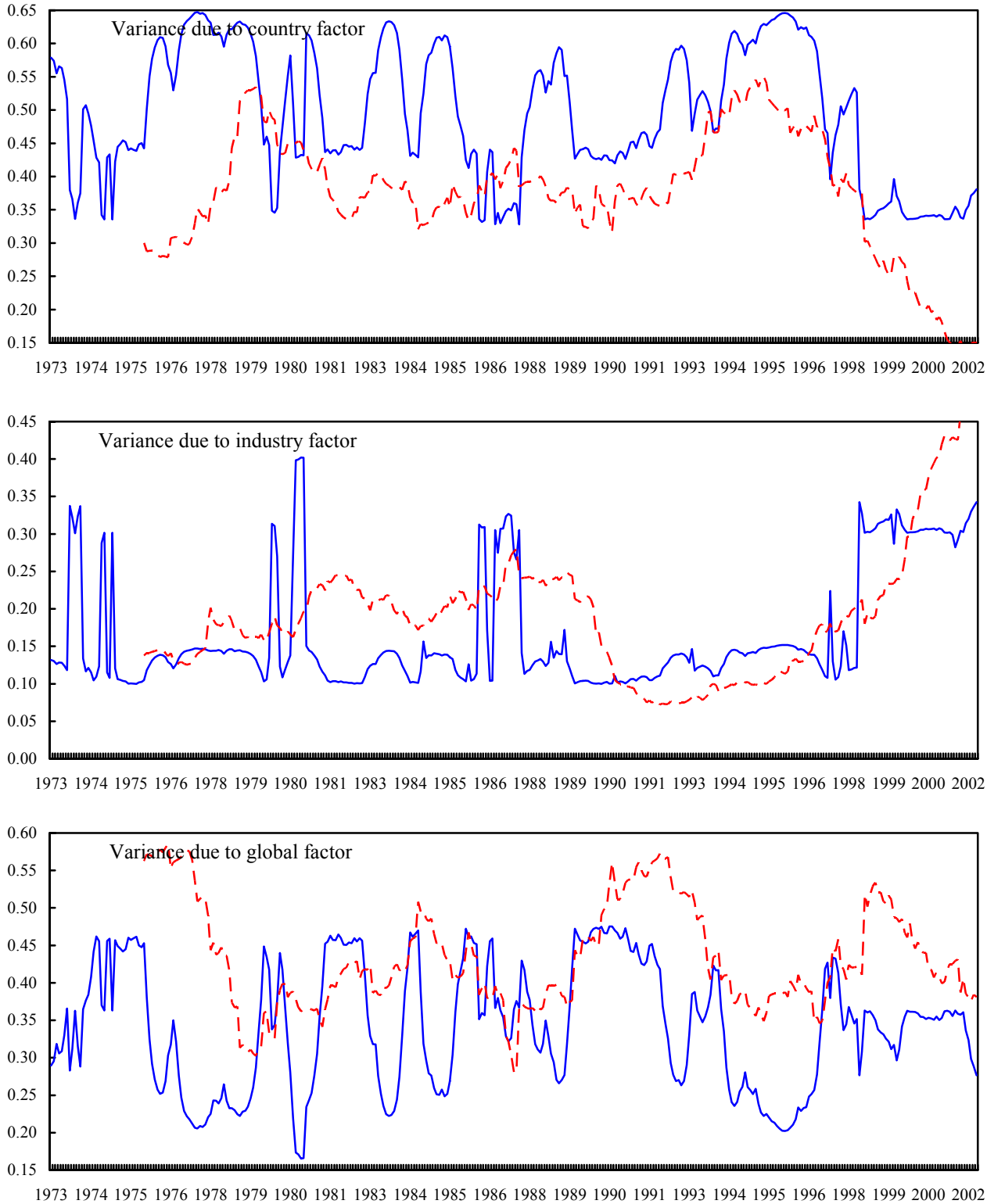

Table 1: Summary Statistics for the Country, Industry, and World Portfolio Returns

	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.