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International Stock Return Comovements

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ABSTRACT

We examine international stock return comovements using country-industry and country-style portfolios as the base portfolios. We first establish that parsimonious risk-based factor models capture the data covariance structure better than the popular Heston–Rouwenhorst (1994) model. We then establish the following stylized facts regarding stock return comovements. First, there is no evidence for an upward trend in return correlations, except for the European stock markets. Second, the increasing importance of industry factors relative to country factors was a short-lived phenomenon. Third, large growth stocks are more correlated across countries than are small value stocks, and the difference has increased over time.

THE STUDY OF comovements between stock returns is at the heart of finance and has recently received much interest in a variety of literatures, especially in international finance. First, recent articles such as Cavaglia, Brightman, and Aked (2000) have challenged the classic result from Heston and Rouwenhorst (1994) that country factors are more important drivers of volatility and comovements than are industry factors. If true, there are important implications for asset management and the benefits of international diversification. Second, it is generally believed that increased capital market integration should go hand-in-hand with increased cross-country correlations. Whereas there has been much empirical work in this area, such as Longin and Solnik (1995), it is fair to say that there is no definitive evidence that cross-country correlations are significantly and permanently higher now than they were, say, 10 years ago. Moreover, while the first and second questions are related, few articles have actually made the link explicitly. Third, the study of correlations has received a boost by well-publicized crises in emerging markets, which seem to create "excessive" correlations between countries that some have termed "contagion." The literature is too wide to survey here, but see the survey articles by Karolyi (2003) or Dungey et al. (2005). In a domestic context, Barberis, Shleifer, and Wurgler (2005) suggest that behavioral factors (for instance, a style clientele

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for large stocks) may induce excessive correlation between stocks, and Kallberg and Pasquariello (2008) test for contagion in U.S. domestic portfolios.

Motivated by these issues, we study the comovements between the returns on country-industry portfolios and country-style portfolios for 23 countries, 26 industries, and nine styles during 1980–2005. During this period, markets are likely to have become more integrated at the world level through increased capital and trade integration. Also, a number of regional developments have likely integrated stock markets at a regional level. These developments include the North American Free Trade Agreement (NAFTA), the emergence of the euro, and increasing economic and financial integration within the European Union. To test whether these developments have led to permanent changes in stock return comovements, we rely on the trend tests of Vogelsang (1998) and Bunzel and Vogelsang (2005).

While we apply our tests to nonparametrically estimated correlation statistics (using high frequency data), we also investigate correlations implied by linear risk-based models with time-varying factor exposures (betas) and time-varying factor volatilities. These models not only provide an alternative look at the trend question, but they also help us to interpret our results. In particular, a low frequency but temporary change in factor volatilities may lead to spurious trends in comovement statistics, whereas increases in global betas are more indicative of permanent changes.

The analysis of the factor models is interesting in its own right. Surprisingly, much of the literature on international stock return comovement imposes strong restrictions of constant, unit betas with respect to a large number of country and industry factors, as in the Heston and Rouwenhorst (1994) model. We contrast the predictions of these models for stock return comovements with our risk-based models. While flexibility in the modeling of betas is essential in a framework where the degree of market integration is changing over time, this may not suffice to capture the underlying structural changes in the various markets. Therefore, in addition to standard models of risk like the Capital Asset Pricing Model (CAPM) and the Fama and French (1993) model, we consider an arbitrage pricing theory (APT) model, where the identity of the important systematic factors may change over time.

Our first new result is that risk-based models fit the stock return comovements between our portfolios much better than the Heston–Rouwenhorst model does. In particular, the APT and a Fama–French (1998) type model with global and regional factors fit the data particularly well. Second, in examining time trends in country return correlations, we find a significant upward trend for stock return correlations only within Europe. Third, we revisit the country-industry debate by examining the relative evolution of correlations across country portfolio returns versus correlations across industry portfolio returns. While industry correlations seem to have decreased in relative terms over the 1990s, this evolution has been halted and reversed, and there is no evidence of a trend. Consequently, despite many recent claims to the contrary, we confirm the Heston–Rouwenhorst (1994) result regarding the primacy of country versus industry factors. Fourth, in examining the correlation between portfolios of similar styles across countries, we find that large growth stocks are more correlated across countries than are small value stocks, and that the difference in correlation has increased over time.

The results above have several important implications for the international finance and diversification literature. First, while our analysis of international stock return comovements reveals significant weaknesses of the Heston–Rouwenhorst model, when viewed as a factor model, we also show that the Heston–Rouwenhorst empirical results regarding the primacy of country factors stand the test of time. Second, all of our results confirm that there still appear to be benefits from international diversification: For many country groups we do not find that significant trends in correlations and country factors still dominate industry factors. Yet, we do see the effects of globalization as well. The correlation trends would suggest that investors in the United States and Europe may benefit more from investments in the Far East, as opposed to in each other's regions, and from investing in small value stocks, as opposed to large growth stocks.

The paper is organized as follows. Section I introduces the data. Section II discusses the various factor models we consider. We choose the best model for comovements in Section III. Section IV provides the salient empirical results using country-industry and country-style portfolios. Section V concludes.

I. Data

We study weekly portfolio returns from 23 developed markets. We choose to study returns at a weekly frequency to avoid the problems caused by nonsynchronous trading around the world at higher frequencies. All returns are U.S. dollar denominated, and we calculate excess returns by subtracting the U.S. weekly T-bill rate, which is obtained from the Center for Research in Security Prices (CRSP) riskfree file.[1] Our selection of developed countries matches the countries currently in the Morgan Stanley Developed Country Index. Data for the United States are from Compustat and CRSP. Data for the other countries are from DataStream. The sample period is 1980:01–2005:12, yielding 1,357 weekly observations.

Table I provides summary statistics for our data. The starting point is usually the beginning of 1980, except for Finland, Greece, New Zealand, Portugal, and Spain, which mostly start in 1986.[2] We require that firms have a market capitalization of more than $1 million. We examine the average of firms' annual return, size, and book-to-market ratio (denoted by BM). There are large differences across countries. For instance, the average firm size is $300 million for Austria and $1,538 million for Japan, and the average BM is 0.71 for Japan

[1] The T-bill rates in CRSP are reported as annualized numbers per month. We convert the rates to weekly numbers by dividing the rate by 52 (number of weeks in 1 year).

[2] DataStream's coverage within various markets is time-varying. For instance, the data set tends to cover larger firms at the beginning of our sample period. Because we use value-weighted index returns throughout the paper, the possible omission of smaller firms should not significantly affect our results.

Table I
Summary Statistics for Firm Returns

All numbers reported are time-series averages (TSAs) for the relevant statistics. The sample period is January 1980–December 2005. For U.S. firms, return and accounting data are obtained from CRSP and Compustat; for other countries, return and accounting data are obtained from DataStream. All the returns are denominated in U.S. dollars. BM stands for the book-to-market ratio.

	Starting Date	Average Firm Return (%)	Average Firm Size ($ mil)	Average Firm BM	Average Number of Firms	Average Total Market Cap ($ bil)	Average% of of Global Market Cap
Canada	1980:01	19.72	599	0.90	489	330	2.7%
France	1980:01	19.42	993	1.05	451	580	3.6%
Germany	1980:01	12.22	1,042	0.80	460	522	4.0%
Italy	1980:01	17.46	1,135	0.92	205	272	1.8%
Japan	1980:01	15.49	1,538	0.71	1,506	2,417	23.7%
United Kingdom	1980:01	17.03	890	0.88	1,142	1,168	9.1%
United States	1980:01	16.72	1,241	0.81	4,013	5,228	44.9%
Australia	1980:01	19.90	571	0.87	417	215	1.5%
Austria	1980:01	14.28	300	1.34	70	26	0.2%
Belgium	1980:01	16.97	640	1.23	92	74	0.5%
Denmark	1980:01	19.26	301	1.64	137	48	0.3%
Finland	1987:01	18.21	776	0.96	104	97	0.5%
Greece	1988:01	26.06	218	0.75	201	55	0.3%
Hong Kong	1980:01	21.50	771	1.25	320	263	1.7%
Ireland	1980:01	21.74	629	1.21	42	31	0.2%
Netherlands	1980:01	16.75	1,663	1.44	126	255	1.6%
New Zealand	1986:01	16.35	395	0.91	55	18	0.1%
Norway	1980:01	21.22	331	1.32	108	45	0.3%
Portugal	1988:01	14.50	512	1.18	70	38	0.2%
Singapore	1980:01	17.56	585	0.91	161	92	0.7%
Spain	1986:01	21.55	1,975	0.89	109	240	1.4%
Sweden	1980:01	19.55	613	0.84	196	144	0.9%
Switzerland	1980:01	12.96	1,376	1.17	189	306	1.9%

and 1.64 for Denmark. These differences motivate portfolio construction within each country.

Our basic assets are value-weighted country-industry and country-style portfolio returns. For the country-industry portfolios, we first need a uniform industry classification. DataStream provides FTSE industry identifications for each firm, while the U.S. industry identification in CRSP is from Standard Industrial Classification (SIC). We group the 30 SIC industries and the 40 level-4 FTSE industry classifications into a smaller number of industries that approaches the number of countries in our sample, resulting in 26 industries. An additional table (available at the *Journal of Finance*'s website: www.afajof.org.) shows the reconciliation between the SIC and the FTSE systems. To form country-industry portfolios, we group firms within each country into these 26 industry groups and calculate a value-weighted return for the portfolio for each period.

The style of a portfolio, value versus growth or small versus big, is a main organizing principle in the U.S. asset management industry. The behavioral finance literature also stresses the potential importance of style classification for stock return comovements. Hence, we also sort firms into different styles according to their size (market capitalization) and their BM ratio. To form country-style portfolios, we use the following procedure. Every 6 months, we sort firms within each country into three size groups and three BM groups, with firm size and BM calculated at the end of the last 6-month period.[3] We then form nine portfolios using the intersections of the size groups and the BM groups. We use a three-by-three approach because of the small number of firms in the smaller countries. The style portfolio level returns are the value-weighted returns of firms in the portfolio. All portfolios are required to have at least five firms.

A preliminary investigation of the raw data reveals that in the 1998–2002 period, a few country portfolios (and the world portfolio) exhibit very high volatility. In particular, the TMT industries (information technology, media, and telecommunication) witnessed a tremendous increase in volatility during that period, as Brooks and Del Negro (2004) document. This increase in volatility is also noticeable for the style portfolios, especially for the small firms. In the last few years of the sample, volatility returns to more normal levels, similar to the volatility levels witnessed in the early part of the sample.

II. Models and Empirical Design

This section first presents a general modeling framework; it then introduces the different model specifications we estimate.

[3] DataStream reports firm book value monthly, while Compustat reports firm book value at each firm's fiscal year end, which can be any time during the year. For U.S. firms, we take the book value that is available at the end of the last 6-month period.

A. General Model

All of our models are special cases of the following data-generating process for the excess return on asset j at time t, $R_{j,t}$:

$$R_{j,t} = E(R_{j,t}) + \left(\beta_{j,t}^{glo}\right)' F_t^{glo} + \left(\beta_{j,t}^{reg}\right)' F_t^{reg} + \epsilon_{j,t}, \tag{1}$$

where $E(R_{j,t})$ is the expected excess return for asset j, $\beta_{j,t}^{glo}$ is a $k^{glo} \times 1$ vector of asset j's loadings on global shocks, F_t^{glo} is a $k^{glo} \times 1$ vector of zero-mean global shocks, $\beta_{j,t}^{reg}$ is a $k^{reg} \times 1$ vector of loadings on regional shocks, and F_t^{reg} is a $k^{reg} \times 1$ vector of zero-mean regional shocks at time t. The general difficulties in inferring expected returns from noisy return data are compounded by the process of gradual market integration potentially characterizing the data. We therefore do not further explore the implications of the factor model for expected returns, and we focus on second moments.

We define a factor to be global if it is constructed from the global capital market, and we define a factor to be regional if it is constructed only from the relevant regional market. In this paper, we consider three regions: North America, Europe, and the Far East. Many articles (see for instance, Bekaert and Harvey (1995) and Baele (2005)) have noted that the market integration process may not proceed smoothly. Therefore, maximum flexibility in the model with regard to the importance of global versus regional factors is necessary. This general model allows time-varying exposures to global and regional factors, potentially capturing full or partial world market integration or regional integration and changes in the degree of integration. We choose to use regional factors rather than country factors as local factors because Brooks and Del Negro (2005) show that within-region country factors can be mostly explained by regional factors. The use of regional factors also reduces the number of factors included in each model.

To identify the time-variation in the betas and factor volatilities, we consider two approaches. In the first approach, we re-estimate the models every 6 months, essentially assuming that for every week t in the τth 6-month period, $\beta_{j,t} = \beta_{j,\tau}$, with $t = 1, 2, \ldots, 1357$, and $\tau = 1, 2, \ldots, 52$ because we have 26 years of data. We then compute the empirical covariance matrix of our portfolios for each 6-month period, generating 52 covariance estimates.[4] In the second approach, we specify a parametric model of betas:

$$\beta_{j,t} = b_{0,j} + b_{1,j} rf_{t-1} + b_{2,j} \sigma_{j,\tau-1}. \tag{2}$$

The interest rate is the 1-week U.S. T-bill rate and $\sigma_{j,\tau-1}$ represents the portfolio's volatility estimated over the previous half year with weekly data. The interest rate captures potential cyclical movements in $\beta_{j,t}$, whereas the dependence on portfolio volatilities captures potential correlations between volatility and beta movements. This model is estimated over the full sample period and

[4] We start the sample in January, but we also re-run our tests using a sample starting each half year on April 1, which yields qualitatively similar results.

is more parsimonious than the first approach. We refer to the first approach as the "time-varying beta" model, and we refer to the second approach as the "conditional beta" model.

While many of our key results only rely on the empirical covariance estimates, the factor model decomposition in betas and factor volatilities helps us interpret the results on long run trends in comovements. In particular, let $F_t = \{(F_t^{glo})', (F_t^{reg})'\}'$ be the $(k^{glo} + k^{reg}) \times 1$ factor vector for week t, let $\Sigma_{F,\tau} = \text{cov}_\tau(F_t, F_t)$ be a $(k^{glo} + k^{reg}) \times (k^{glo} + k^{reg})$ factor covariance matrix for the τth 6-month period, and let $\beta_{j,\tau} = \{(\beta_{j,\tau}^{glo})', (\beta_{j,\tau}^{reg})'\}'$ be a $(k^{glo} + k^{reg}) \times 1$ loading vector for the τth 6-month period. In the first approach of "time-varying beta," the covariance of two returns, R_{j1}, R_{j2} $(j1 \neq j2)$, can be written as a function of the factor loadings and variances, plus a residual covariance:

$$\text{cov}_\tau(R_{j1}, R_{j2}) = \beta'_{j1,\tau} \Sigma_{F,\tau} \beta_{j2,\tau} + \text{cov}_\tau(\epsilon_{j1}, \epsilon_{j2}). \tag{3}$$

In the second approach of "conditional beta," we can similarly calculate model-implied covariance estimates for each τth 6-month period, using

$$\text{cov}_\tau(R_{j1}, R_{j2}) = \text{cov}_\tau\left(\beta'_{j1,t} F_t, \beta'_{j2,t} F_t\right) + \text{cov}_\tau(\epsilon_{j1}, \epsilon_{j2}), \tag{4}$$

where the covariance on the right-hand side is a simple sample estimate. If the factor model fully describes stock return comovements, the residual covariance $\text{cov}_\tau(\epsilon_{j1}, \epsilon_{j2})$ should be zero.

Assuming the residual covariances to be zero, equation (3) shows that covariances between two assets estimated in different periods can increase through the following two channels: an increase in the factor loadings β and/or an increase in factor covariances Σ_F. If the increase in covariance is due to increased exposure to the world market (β^{glo}), as opposed to an increase in factor volatilities (Σ_F), the change in covariance is much more likely to be associated with the process of global market integration (and thus to be permanent or at least very persistent). Analogously, correlations are covariances divided by the product of the volatilities of the asset returns involved. Correlations are increasing in betas and factor volatilities, but they are decreasing in idiosyncratic volatility, everything else equal. Because the volatility of the market portfolio, while varying over time, shows no long-term trend (see Schwert (1989)), it is very important to control for the level of market volatility when assessing changes in correlations. As we will show below, many of the empirical results in the literature fail to account for the likely temporary increase in factor volatilities occurring at the end of the previous century. Such a decomposition is not possible with the conditional beta model as it allows betas and factor variances to correlate within each 6-month period.

B. CAPM Models

The CAPM models use market portfolio returns as the only relevant factors:

$$R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WMKT} WMKT_t + \beta_{j,t}^{LMKT} LMKT_t + \epsilon_{j,t}. \tag{5}$$

where *WMKT* is calculated as the demeaned value-weighted sum of returns on all country-industry (or country-style) portfolios. We calculate the local factor *LMKT* in two stages. First, we compute the demeaned value-weighted sum of returns on all country-industry (or country-style) portfolios within the region. Next, we orthogonalize this return with respect to *WMKT* using an ordinary least square regression on *WMKT*. The error term of the regression is the new region-specific *LMKT*. This regression is conducted every 6 months to allow for time-varying factor loadings. Note that the orthogonalization simplifies the interpretation of the betas, but it does not otherwise affect the model. This partial integration model is designated as the WLCAPM. The special case for which $\beta_{j,t}^{LMKT}$ is zero is the world CAPM, denoted WCAPM. This model only holds if the world capital market is perfectly integrated.

C. Fama-French Models

Stock return comovements may also be related to the style of the stocks involved, that is, small versus large or value versus growth stocks. Whether these comovements are related to their cash flow characteristics or the way these stocks are priced remains an open question. We add a size factor to the parsimonious factor model proposed by Fama and French (1998) to capture style exposures in an international context. The world Fama-French model, WFF, has three factors, namely a market factor (*WMKT*), a size factor (*WSMB*), and a value factor (*WHML*). The world-local Fama-French model (WLFF), incorporates regional factors in addition to global factors:

$$\begin{aligned} R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WMKT} WMKT_t + \beta_{j,t}^{WSMB} WSMB_t + \beta_{j,t}^{WHML} WHML_t \\ + \beta_{j,t}^{LMKT} LMKT_t + \beta_{j,t}^{LSMB} LSMB_t + \beta_{j,t}^{LHML} LHML_t + \epsilon_{j,t}. \end{aligned} \tag{6}$$

Consequently, the WFF model imposes $\beta_{j,t}^{LMKT} = \beta_{j,t}^{LSMB} = \beta_{j,t}^{LHML} = 0$. To calculate *WSMB*, we first compute *SMB*(k) for each country k, which is the difference between the value-weighted returns of the smallest 30% of firms and the largest 30% of firms within country k. The factor *WSMB* is the demeaned value-weighted sum of individual country *SMB*(k)s. The factor *WHML* is calculated in a similar way as the demeaned value-weighted sum of individual country *HML*(k)s using high versus low book-to-market values. The local factors (*LMKT*, *LSMB*, *LHML*) are all orthogonalized relative to the global factors (*WMKT*, *WSMB*, *WHML*). We do not orthorgonalize among the local or global factors, so it is possible that, for instance, *LMKT* has a nonzero correlation with *LSMB*.

D. APT Models

The APT models postulate that pervasive factors affect returns. To find comprehensive factors relevant for the covariance structure, we extract APT factors from the covariance matrix of individual portfolio returns, using Jones's (2001) methodology. Jones (2001) modifies the empirical procedure of Conner and Korajczyk (1986) to incorporate time-series heteroskedasticity in the residuals.[5] We denote the global version of the model by WAPT, and the partial integration version of the WAPT by WLAPT:

$$R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WPC1} WPC1_t + \beta_{j,t}^{WPC2} WPC2_t + \beta_{j,t}^{WPC3} WPC3_t + \beta_{j,t}^{LPC1} LPC1_t + \beta_{j,t}^{LPC2} LPC2_t + \beta_{j,t}^{LPC3} LPC3_t + \epsilon_{j,t}, \quad (7)$$

where $WPC1$, $WPC2$, and $WPC3$ are the first three principal components from the factor analysis, and $LPC1, LPC2$, and $LPC3$ are the first three principal components for the relevant region. We estimate the covariance matrix, and extract the principal components (factors) every half year, using the 26 weekly returns for all individual portfolios. By construction, the factors have zero means and unit volatilities, and they are orthogonal to each other. This procedure allows the factor structure to change every half year, implicitly accommodating time-varying risk prices and risk loadings (betas). We use the first three factors to be comparable with the Fama-French model, and we find that the three factors explain a substantial amount (50% to 60%) of the time-series variation of returns. The regional factors are first extracted using portfolios within each region and then the LPCs are orthogonalized with respect to the WPCs. We estimate the factor loadings for each 6-month period, with $\beta_{j,t}^{LPC1} = \beta_{j,t}^{LPC2} = \beta_{j,t}^{LPC3} = 0$ for the WAPT model.

E. Heston and Rouwenhorst Model

Heston and Rouwenhorst (1994) propose a dummy variable model, which is widely used in the country-industry literature. Let there be n_{cou} countries and n_{ind} industries. The model posits that a portfolio j (belonging to country c and industry i) receives a unit weight on the market return, a unit weight on country c, and a unit weight on industry i. Thus, returns for period t are determined by

$$R_{j,t} = \alpha_t + D'_{C,j} * C_t + D'_{I,j} * I_t + \epsilon_{i,t}. \quad (8)$$

The variable $D_{C,j}$ is an $n_{cou} \times 1$ country dummy vector, with the c-th element equal to one, and the variable C_t is an $n_{cou} \times 1$ country effect vector. The variable $D_{I,j}$ is an $n_{ind} \times 1$ industry dummy vector, with the i-th element equal to one, and the variable I_t is an $n_{ind} \times 1$ industry effect vector. To estimate this model, one must impose additional restrictions: $\sum_{l=1}^{n_{cou}} w_{C,l} C_l = 0$, and $\sum_{l=1}^{n_{ind}} w_{I,l} I_l = 0$, where $w_{C,l}$ is the market-capitalization-based country weight for the l-th

[5] The asymptotic principal components procedure described in Conner and Korajczyk (1986) allows for non-Gaussian returns and time-varying factor risk premia. However, Conner and Korajczyk's approach assumes that the covariance matrix of the factor model residuals is constant over time. Jones (2001) generalizes Conner and Korajczyk's procedure by allowing the covariance matrix of the factor model residuals to be time-varying. This generalization complicates the estimation of the principal components, which Jones (2001) resolves using Joreskog's (1967) iterative algorithm.

country and $w_{I,l}$ is the market-capitalization-based industry weight on the l-th industry. With the above restrictions, the intercept α_t is the return on the value-weighted market return at t, $WMKT_t$. We estimate a cross-sectional regression each week in the sample to extract C_t and I_t. The covariance between assets $j1$ and $j2$ for a 6-month period consequently depends only on their respective country and industry memberships:

$$\text{cov}(R_{j1}, R_{j2}) = \text{cov}(WMKT + C_{j1} + I_{j1}, WMKT + C_{j2} + I_{j2}) + \text{cov}(\epsilon_{j1}, \epsilon_{j2}). \tag{9}$$

We denote the model by DCI to indicate the use of dummies for countries and industries.[6] The DCI model is essentially a linear factor model with a large number of factors (a world factor and industry and country factors) and unit exposures to the risk factors. The model intuitively separates returns into country and industry effects and allows one to determine whether country or industry effects dominate the variance of international portfolios. The relative importance of country and industry factors can vary over time as factor realizations change.

The DCI model's major disadvantage is that it assumes all the portfolios within the same country or industry have the same (unit) loadings on the country and industry factors. This makes the model ill-suited to adequately capture and interpret the time-variation in stock return comovements over the last 20 years. The process of global and regional market integration that has characterized global capital markets in the last few decades should naturally lead to time-varying betas with respect to the world market return and/or country-specific factors. If this time-variation is not allowed, it will spuriously affect the industry or factor realizations.

III. Model Selection

In this section, we determine which model provides the best fit for the sample covariance structure. To this end, we first estimate the sample covariance matrix for every half year in the sample, which we denote by $\text{cov}_{sample,\tau}$, $\tau = 1, \ldots, 52$. Given our factor model set-up (see equation (1)), we can decompose the sample covariance into two components. The first component represents the covariances between portfolios driven by their common exposures to risk factors, and the second component represents residual or idiosyncractic comovements:

$$\text{cov}_{sample,\tau} = \text{cov}_{model,\tau} + \text{cov}_{\epsilon,\tau}, \tag{10}$$

where each element in $\text{cov}_{model,\tau}$ follows from equation (3) or (4). The factor models only have testable implications for covariances, so we make the diagonal elements in $\text{cov}_{model,\tau}$ contain sample variances. If the factor model is true, the common factors should explain as much as possible of the sample covariance

[6] We also examine restricted versions of the DCI model: Restricting all country (industry) effects, $C_t(I_t)$, to be zero, we obtain a country-effects-only (industry-effects-only) model.

matrix and the residual covariance components should be zero. In small samples, this may not necessarily be the case even if the model is true, but in the APT model, the residual covariances should tend to zero asymptotically (see Chamberlain (1983) and Chamberlain and Rothschild (1983)). We can define $CORR_{sample,\tau}$, $CORR_{model,\tau}$, and $CORR_{\epsilon,\tau}$ analogously, by dividing each element of all the components in the covariance matrix by $[\mathrm{var}_\tau(R_i)\mathrm{var}_\tau(R_j)]^{0.5}$.

To examine the performance of each model relative to the other models, we use a mean squared error criterion, which is the time-series mean of a weighted average of squared errors,

$$\begin{aligned} MSE_{CORR} &= \frac{1}{52}\sum_{\tau=1}^{52}\left\{\frac{1}{\overline{W_\tau}}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}[CORR_{sample,\tau}(R_{j1,t}, R_{j2,t})\right. \\ &\qquad \left. - CORR_{model,\tau}(R_{j1,t}, R_{j2,t})]^2\right\} \\ &= \frac{1}{52}\sum_{\tau=1}^{52} SE_\tau(\text{model}), \end{aligned} \tag{11}$$

where t indexes different weeks; τ indexes different 6-month periods; $\overline{W_\tau} = \sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}$, a scalar that makes the weights add up to one; and individual portfolio weights are determined by the portfolio's market capitalization from the previous month. This statistic is the Frobenius norm of the difference between the sample and the model correlation matrix (see Ledoit and Wolf (2003)), and its square root is the root mean squared error (*RMSE*) for correlations. We choose to present statistics for correlations rather than covariances for ease of interpretation, but our results for covariances are qualitatively similar.

Section III.A seeks to determine the best fitting model, whereas Section III.B gives an idea of how various features of our factor models affect their ability to match the sample covariance matrix. Section III.C examines the out-of-sample performance of the best models.

A. Minimizing RMSE

Table II reports the model comparison results using MSE_{CORR}. Every cell of the matrix presents the t-statistic testing the significance of $diff(i, j) = MSE(\text{model } i) - MSE(\text{model } j) = \frac{1}{52}\sum_{\tau=1}^{52}[SE_\tau(\text{model } i) - SE_\tau(\text{model } j)] = \frac{1}{52}\sum_{\tau=1}^{52} diff_\tau(i, j)$. We adjust standard errors using the Newey and West (1987) approach with four lags. Given that we only have 52 time-series observations to construct $diff(i,j)$ for each model comparison, the finite sample distribution may be poorly approximated by a normal distribution. We therefore conduct a simple bootstrap analysis. Our pool of possible observations is all possible $diff_\tau(i,j)$ for all i, j, τ. Because both $diff(i,j)$ and $diff(j,i)$ are included, the population distribution has mean zero by construction. We then draw 1,000 samples

Table II

Model Fit: Matching the Sample Portfolio Correlation Matrix

Every cell (i,j) reports the t-statistic for MSE(model i) – MSE(model j). The MSE statistic is defined in equation (11). The standard errors accommodate four Newey-West (1987) lags. An ($*$) indicates that the t-statistic is significant at the 5% level when we use a bootstrapped empirical distribution for the t-statistic. Model WCAPM is the global CAPM, in which the only factor is the global market portfolio return. Model WFF is the global Fama-French three-factor model, in which the factors are the global market portfolio return, the global SMB portfolio, and the global HML portfolio. Model WAPT is the global APT model with three factors. The models WLCAPM, WLFF, and WLAPT include both local factors and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. Model DCI/DCS uses the dummy variable approach in Heston and Rouwenhorst (1994). Panels A and B show results for country-industry and country-style portfolios, respectively. Panel C uses country-industry portfolios to examine the performance of the conditional beta factor model relative to the other models.

Panel A: Country-Industry Portfolio Correlation Matrix

t-Stat Model i	Model j WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT
WLCAPM	−5.50*					
WFF	−6.77*	2.99*				
WLFF	−7.53*	−8.52*	−5.53*			
WAPT	−3.10*	4.07*	−0.56	7.64*		
WLAPT	−7.38*	−7.74*	−5.38*	0.80	−8.38*	
DCI	−2.84*	5.00*	−0.29	7.28*	0.29	7.31*

Panel B: Country-Style Portfolio Correlation Matrix

t-Stat Model i	Model j WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT
WLCAPM	−6.28*					
WFF	−4.92*	4.75*				
WLFF	−6.85*	−6.60*	−5.89*			
WAPT	−4.04*	5.39*	−2.14	7.38*		
WLAPT	−6.33*	−4.57*	−5.30*	2.33*	−7.16*	
DCS	−3.62*	4.31*	−2.16*	6.27*	−1.08	6.25*

Panel C: Conditional Factor Models

t-Stat Model i	Model j WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI
Conditional beta	2.44	6.21*	4.25*	7.13*	5.00*	6.93*	4.79*

of 52 observations (with replacement) out of the pool to create an empirical distribution of the t-statistic. The empirical distribution is rather well behaved with the absolute value of the critical value for a 5% two-sided test being 2.15 (instead of 1.96).[7]

Panel A presents results for country-industry portfolios. For example, between WLCAPM (model i) and WCAPM (model j) (third row, second column),

[7] Alternatively, we create an empirical distribution for each model comparison sampling from its own set of observations (with replacement). Using these distributions leads to the same conclusions.

the t-statistic is -5.50, which indicates that WLCAPM has a significantly lower *MSE* than WCAPM. We find the same pattern between WFF and WLFF, and between WAPT and WLAPT. Hence, the data indicate that partial integration models with regional factors better match the sample covariance structure than full integration models. Comparing the different factor specifications, we find that WLFF is significantly better than WLCAPM ($t = -8.52$), indicating that including the Fama-French factors significantly improves upon the market model. The WLAPT model is also significantly better than the WLCAPM ($t = -7.74$). Although the WLFF model beats the WLAPT, the improvement is not significant.

The last three rows provide results for the dummy variable models. The dummy variable models are always worse than the factor models with two exceptions. The DCI model is significantly better than the WCAPM, and it is better, but not significantly so, than the WFF. For country-style portfolios in Panel B, the results are qualitatively and quantitatively similar to the results for country-industry portfolios.

In Panel C, we compare the *MSE* of the WLFF model with conditional betas, as in equation (2), with the *MSE* of all models with time-varying betas. We only present the WLFF model with conditional betas because it performs the best among conditional beta models. Yet, even this best conditional beta model is dominated by all time-varying beta models and the dummy variable model. Thus, we do not further report additional results for the conditional beta model. Although Ghysels (1998) has found that the constant beta model may perform better (produce lower pricing errors) than conditional beta models because of misspecification in the betas, we show in the next section that the time-varying beta approach outperforms constant beta models.

We consider two robustness checks on the main results. This is particularly important because the covariance matrix estimation problem underlying the results in Table II suffers from an obvious degrees of freedom problem.[8] The first robustness exercise considers five different subsets of the country-industry (or country-style) space and repeats the analysis in Table II. The WLFF and WLAPT models remain either the best or second-best model. The only exception is a case where we look at extreme style portfolios in four small Far East countries. For that case, the WLFF model does relatively worse, but the WLAPT model remains the best model.

In a second exercise, we apply our various models to four firms, chosen from different countries, different industries, and different styles. Again, the WLFF/WLAPT models better match the comovement dynamics between these firms than the dummy models do.

[8] Because we have 23 countries and 26 industries, the covariance matrix dimension is $(23 \times 26) = 598$. This means that we have $598 \times 599/2 = 179{,}101$ different elements for each covariance matrix. Meanwhile, the data points we have are (26 weeks) $\times$ (23 countries) $\times$ (26 industries)=15,548, which is far less than the number of statistics we estimate. Results for the robustness exercises can be found in the Internet Appendix at the *Journal of Finance* website: http://www.afajof.org/supplements.asp.

Because the WLAPT model robustly provides the best match with the sample covariance matrix, we select the WLAPT to be the benchmark model for subsequent analysis. The WLFF model is only slightly worse than the WLAPT model, so we use it as a robustness check.

B. Correlation Errors and the Role of Beta Variation

The value-weighted average portfolio-level correlation in the data is 0.37 for country-industry portfolios and 0.45 for country-style portfolios.[9] Table III presents $RMSE_{CORR}$ for the different models under different assumptions on the time-variation and cross-sectional variation in betas. In the first column of Panel A in Table III, we start with a unit-beta world CAPM model as a benchmark. That is, we assume $\beta^{WMKT} = 1$ and $\beta^{LMKT} = 0$ in equation (5). The unit beta model generates correlations that are on average much too low, leading to a *RMSE* of 0.362. We then set β^{WMKT} equal to the cross-sectional average beta value within each period. The results are presented in the first row of the second and third columns. Restricting all the portfolios to have the same market risk exposure within each period barely improves the model's ability to match the sample correlations, and the *RMSE* is still at 92% of that of the unit beta model. The next experiment sets β_{WMKT} equal to the time-series average (TSA) beta for the individual portfolios. The numbers are presented in the first row of the fourth and fifth columns. Now, with cross-sectional differences across portfolios but no time-series variation, the model slightly improves on the unit beta model (85% of the unit beta model's error), but the *RMSE* is still as large as 0.309. If we allow β_{WMKT} to vary both cross-sectionally and over time, as in the first row of the sixth and seventh columns, the *RMSE* statistic drops to 0.206, only 57% of the error produced by the unit beta model.

The second through sixth rows explore whether other factors (such as FF and APT factors, or local factors) help in matching the sample correlations. For the Fama-French and APT models, fixing the factor loadings to their time-series or cross-sectional averages also prevents them from matching the sample correlations. If we allow the betas to vary over time and cross-sectionally, as in the sixth and seventh columns, the *RMSE* measure decreases to 0.174 for the WFF model and 0.166 for the WAPT model. Consequently, despite the fact that the time-varying betas are estimated with considerable sampling error, they nonetheless are very valuable in improving the fit of the model. If we include regional (local) factors, the *RMSE* measure decreases to 0.086 for the WLFF model and to 0.088 for the WLAPT model. Hence, the Fama-French and APT models featuring regional factors miss the correlation on average only by around 0.08.

In comparison, the *RMSE* of the Heston–Rouwenhorst model is 0.169, which is lower than the WCAPM's error of 0.206, but higher than that of the WL-CAPM model. In conclusion, to match correlations, allowing free loadings on the world market portfolios and the regional factors is more effective than including

[9] Using equally weighted correlations does not affect any of our empirical results.

Table III

Model Fit: The Role of Betas and Multiple Factors

This table reports the RMSE for the various estimated models, both unrestricted and with restrictions on the betas. The RMSE measure is the square root of the MSE statistic, defined in equation (11). Unit beta means the global market beta is set to one. Cross-sectional average beta means that all the betas in each model are set to the cross-sectional average of betas within each 6-month period. TSA beta means that all the betas in each model are set to the time series average for each country-industry (or style) portfolio. Free beta means there are no restrictions. Model WCAPM is the global CAPM, in which the only factor is the global market portfolio return. Model WFF is the global Fama-French three-factor model, in which the factors are the global market portfolio return, the global SMB portfolio, and the global HML portfolio. Model WAPT is the global APT model with three factors. The models WLCAPM, WLFF, and WLAPT include both local factors and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. Model DCI/DCS uses the dummy variable approach from Heston and Rouwenhorst (1994).

		Cross-section Average Betas		TSA Betas		Free Beta	
	Unit Beta RMSE	RMSE	Percent of Unit Beta RMSE (%)	RMSE	Percent of Unit Beta RMSE (%)	RMSE	Percent of Unit Beta RMSE (%)
Panel A: Country-Industry Portfolios							
WCAPM	0.362	0.332	92	0.309	85	0.206	57
WLCAPM		0.342	94	0.280	77	0.129	36
WFF		0.335	92	0.309	85	0.174	48
WLFF		0.349	96	0.281	78	0.086	24
WAPT		0.352	97	0.448	124	0.166	46
WLAPT		0.354	98	0.443	122	0.088	24
DCI						0.169	47
Panel B: Country-Style Portfolios							
WCAPM	0.378	0.359	95	0.334	89	0.215	57
WLCAPM		0.362	96	0.295	78	0.099	26
WFF		0.346	92	0.335	89	0.186	49
WLFF		0.364	96	0.296	78	0.058	15
WAPT		0.375	99	0.507	134	0.155	41
WLAPT		0.376	99	0.501	133	0.068	18
DCS						0.141	37

country and industry dummies. More generally, the Heston–Rouwenhorst model on average produces an error that is better than any risk model with only world factors, but worse than any parsimonious risk model with regional factors. Our results suggest that technical advances modifying the Heston–Rouwenhorst approach to allow for non-unitary but time-invariant betas (as in Marsh and Pfleiderer (1997) and Brooks and Del Negro (2005)) would not appear very helpful in improving the model's fit.

While our results suggest that the Heston–Rouwenhorst model does not provide the best fit with stock return comovements, it has dominated the important country-industry debate. As a brief review, while it was long believed that country factors dominated international stock return comovements (see

Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998)), a number of relatively recent articles argue that industry factors have become more dominant (see Cavaglia, Brightman, and Aked (2000) and Baca, Garbe, and Weiss (2000)). The most recent articles provide a more subtle but still conflicting interpretation of the data. Brooks and Del Negro (2004) find that the TMT sector accounts for most of the increasing importance of industry factors, and argue that the phenomenon is likely a temporary phenomenon. However, Ferreira and Gama (2005) argue that country risk remained relatively stable over their sample period but industry risk rose considerably while correlations between industry portfolios decreased. They claim this phenomenon is not simply due to the TMT sector.[10] Finally, Carrieri, Errunza, and Sarkissian (2008) claim that there has been a gradual increase in the importance of industry factors. In unreported results, we find that shutting down industry factors within the Heston–Rouwenhorst model leads to smaller errors than shutting down the country factors. In Section IV, we revisit this debate using correlation statistics to show that country factors remain more important than industry factors.

Panel B performs the same computations for country-style portfolios. The results are quite similar. The WLFF model has the best overall fit and fits the correlations better than a dummy style model. The largest relative contribution comes from allowing both time-variation and cross-sectional variation in betas. It is striking that a unit beta global CAPM model fits the correlations about as well as the style dummy model.

C. Out-of-Sample Fit of Factor Models

It is perhaps no surprise that the flexible WLAPT model provides the best fit with stock return comovements in sample. Two additional results stand out. First, the WLFF model most closely matches the performance of the WLAPT model, and in some cases performs even better. Second, even simple risk-based models perform better or at least as well as the popular Heston–Rouwenhorst model. In this section, we test whether the time-varying beta models are also useful out-of-sample. Our approach closely follows the methodology in Ledoit and Wolf (2003) to test the out-of-sample performance of various factor models. First, for each half year, we compute the candidate covariance matrices, $\widehat{V}_k$, where k indexes our various models, and we compute the corresponding global minimum variance portfolio for the particular space of assets: $w_k = \frac{\widehat{V}_k^{-1\prime}e}{e'\widehat{V}_k^{-1}e}$, where e is a vector of ones. Note that we use the model only to compute covariances, and we use the sample variances along the diagonal. Moreover, this portfolio does not depend on expected returns. For large asset spaces, using the sample covariance matrix to estimate V is ill-advised because of the dimensionality problem mentioned earlier. We verified that the sample covariance matrix typically had a huge condition number and was practically not

[10] De Roon, Eiling, Gerard, and Hillion (2006) look at the industry-country debate from the perspective of mean variance spanning tests and style analysis. They find that country factors remain dominant. Catao and Timmerman (2009), using the Heston–Rouwenhorst model, argue that the relative importance of country factors is related to global market volatility.

Table IV

Out-of-Sample Performance Using Global Minimum Variance Portfolios

For each half year, we compute the candidate variance–covariance matrices based on each model, and we compute the corresponding global minimum variance portfolio. We use the sample variances along the diagonal for the covariance matrix. We hold this portfolio during the next 6 months and compute its volatility using weekly returns. We repeat these steps for each 6-month period and average the computed volatilities over the full sample. Model WCAPM is the global CAPM, in which the only factor is the global market portfolio return. Model WFF is the global Fama-French three-factor model, in which the factors are the global market portfolio return, the global SMB portfolio, and the global HML portfolio. Model WAPT is the global APT model with three factors. The models WLCAPM, WLFF, and WLAPT include both local factors and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. Model DCI/DCS uses the dummy variable approach from Heston and Rouwenhorst (1994). The row labeled as "all EW (all VW)" is a benchmark case, where we compute the variance of an equal-weighted (value-weighted) portfolio of all country-industry or country-style portfolios. The row labeled "U.S. EW (U.S. VW)" only includes U.S. portfolios.

	Case I: Country Industry Portfolios	Case II: Country Style Portfolios
WCAPM	0.0994	0.0970
WLCAPM	0.0964	0.0933
WFF	0.0980	0.0956
WLFF	0.0961	0.0946
WAPT	0.0970	0.0934
WLAPT	0.0974	0.0949
DCI/DCS	0.1130	0.1128
All EW	0.1180	0.1139
All VW	0.1294	0.1291
U.S. EW	0.1419	0.1467
U.S. VW	0.1447	0.1447

invertible. Second, we hold this portfolio during the next 6 months and compute its volatility using weekly returns. Third, we repeat these steps for each 6-month period and average the computed volatilities over the full sample. Naturally, the best out-of-sample model for capturing comovements should minimize the realized volatility.[11]

We report the results in Table IV. First, the risk-based models perform uniformly and considerably better than the Heston–Rouwenhorst models, producing average volatilities that are well over 1% lower. Second, the WLFF model is the best model for the country-industry portfolios, but the WLCAPM is the best for the country-style portfolios. However, the performance of all risk-based models is quite close. The estimation noise in the betas likely adversely affects the out-of-sample performance of the less parsimonious models. Because we only use the factor model to help interpret results regarding trends in comovements, we continue to use the WLAPT and WLFF models.

[11] Robustness checks for more limited asset spaces are available in the Internet Appendix at the *Journal of Finance* website: http://www.afajof.org/supplements.asp.

The last four lines of the table demonstrate the potential usefulness of the risk models for portfolio choice, and fit nicely into our main results for the trend analysis. The "all EW" and "all VW" rows show that simple diversification strategies, using equally weighted or value-weighted portfolios, generate much higher volatility than the optimized portfolios using risk-based covariances, but they are only slightly worse than the Heston–Rouwenhorst model portfolios. This strongly suggests that our models can help maximize the benefits of international diversification. The last two rows investigate U.S.-based portfolios to quantify the average volatility benefits of international diversification. Clearly, international diversification has significantly reduced portfolio risk, on average, over the sample. Using country-industry portfolios, the U.S. EW portfolio is 2% more variable than a naively internationally diversified one, such as the "all EW" portfolio, and almost 4.5% more volatile than an optimally diversified one using the best risk-based model, the WLFF model. In the next section, we demonstrate that overall the trends in correlations are less strong than generally believed, suggesting these benefits remain important.

IV. Trends in Comovements

In this section, we study long-run movements in correlations to address several salient empirical questions in the international finance literature. We start, in Section IV.A, with a discussion of the general methodology, which we apply to our base portfolios. In Section IV.B, we consider the long-run behavior of correlations between country returns, addressing the question of whether globalization has indeed caused international return correlations to increase over the 1980–2005 period. We devote special attention to correlation dynamics within Europe. In Section IV.C, we consider the implications of our analysis for the country-industry debate. In Section IV.D, we further investigate the role of style as a driver of international return correlations. In Section IV.E, we link our framework briefly to the contagion literature, and the recent debate about trends in idiosyncratic variances.

A. Methodology and Trends in Base Portfolio Correlations

We begin by defining the following comovement measures for average portfolio-level covariances:

$$
\begin{aligned}
\gamma^{\text{cov}}_{sample,\tau} &= \frac{1}{W_\tau}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}\,\text{cov}_\tau(R_{j1,t}, R_{j2,t}) \\
&= \frac{1}{W_\tau}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}\,\text{cov}_\tau(\beta'_{j1}F_t, \beta'_{j2}F_t) \\
&\quad + \frac{1}{W_\tau}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}\,\text{cov}_\tau(\epsilon_{j1,t}, \epsilon_{j2,t}) \\
&= \gamma^{\text{cov}}_{risk,\tau} + \gamma^{\text{cov}}_{idio,\tau},
\end{aligned}
\tag{12}
$$

where $\overline{W_\tau} = \sum_{j1=1}^{n_{PORT}} \sum_{j2=1, j1\neq j2}^{n_{PORT}} w_{j1,\tau} w_{j2,\tau}$ is a scalar that makes the weights add up to one. For ease of interpretation, we focus on the same decomposition for correlations, where

$$\gamma_{sample,\tau}^{CORR} = \gamma_{risk,\tau}^{CORR} + \gamma_{idio,\tau}^{CORR}. \tag{13}$$

Figure 1 presents the time series of γ_{sample}^{CORR}, γ_{risk}^{CORR}, and γ_{idio}^{CORR} for country-industry (Panel A) and country-style portfolio (Panel B) correlations. The benchmark model for the decomposition is the WLFF model because it allows us to disentangle the sources of the time-variation in comovements in terms of time-variation in betas versus time-variation in factor covariances. Overall, the model closely matches the time series of average portfolio-level correlations. Reflecting this good fit, the residual correlations at the bottom of each figure are small in terms of magnitude (less than 0.10). Therefore, we do not report tests concerning these residual comovements.

The main goal of our empirical work is to assess whether correlations display trending behavior (as brought about by the process of globalization, for example). We therefore conduct trend tests on both γ_{sample}^{CORR} and γ_{risk}^{CORR}. There are two main reasons to include correlations implied by the factor models. First, as discussed above, the factor model can be used to help interpret the trend results in terms of their underlying sources (beta or factor volatility changes). Second, the best models (WLAPT, WLFF) fit the data well and circumvent the dimensionality problem plaguing the estimation of the sample covariance estimator.

To formally test for trends, we use Vogelsang's (1998) simple linear time trend test. The benchmark model is defined to be

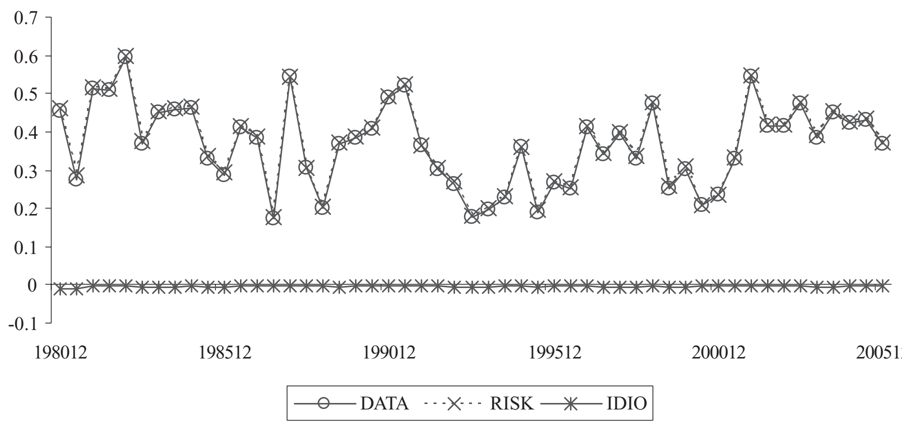
$$y_\tau = \alpha_0 + \alpha_1 \tau + u_\tau, \tag{14}$$

where y_τ is the variable of interest and τ is a linear time trend. We use the PS1 test in Vogelsang to test $\alpha_1 = 0$. The test statistic is robust to $I(0)$ and $I(1)$ error terms.[12]

In all of the ensuing tables, we report the trend coefficient, the t-statistic, and the 5% critical value derived in Vogelsang (1998) (for a two-sided test). We also report the critical value for a 5% one-sided test as the most likely alternative hypothesis is that correlations have increased (see further). While Vogelsang's test has good size and power properties, our relatively small sample necessitates the use of a powerful test. Bunzel and Vogelsang (2005) develop a test that retains the good size properties of the PS1 test, but it has better power (both asymptotically and in finite samples). We denote this test with a "dan" subscript, as the test uses a "Daniell kernel" to nonparametrically estimate the error variance needed in the test. In fact, tests based on this kernel maximize power among a wide range of kernels.

[12] Before the trend test, we conduct unit root tests following Dickey and Fuller (1979). Our null hypothesis includes both a drift and a time trend. We strongly reject the null hypothesis that our covariance and correlation measures contain a unit root.

Panel A: Decomposition for Country-Industry Portfolios



Panel B: Decomposition for Country-Style Portfolios

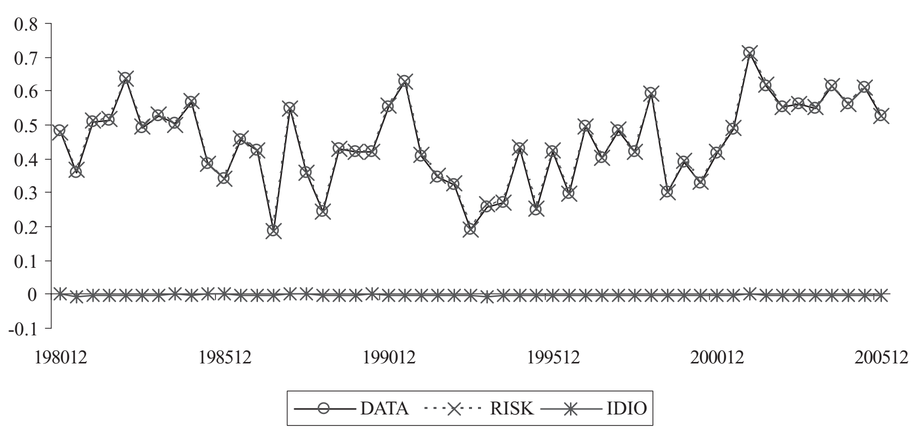


Figure 1. Time series of portfolio-level correlation measure. The data correlation and its decomposition are defined in equation (13), where DATA refers to γ^{CORR}_{sample}, RISK refers to γ^{CORR}_{risk}, and IDIO refers to the difference between the two or γ^{CORR}_{idio}. The sample period is January 1980–December 2005.

Table V contains our main results. We report statistics for the correlation measure for country-industry portfolios in Panel A and for country-style portfolios in Panel B. We investigate the sample and model comovement measures and two alternative measures, computed by either setting the loadings $B_{j\tau}$ or the factor covariance matrix Σ_{F_τ} to their sample means, denoted as TSA (time-series average) beta and TSA factor covariance, respectively. We implement this restriction both in the numerator (covariance) and in the denominator (variance). Factor volatilities show substantial time-variation, but permanent trend changes in comovements are likely to come from changes in betas (for instance, relative to global factors). This decomposition sheds light on the sources of

Table V

Long-Term Movements in Correlations: Base Portfolios

We report time-series properties for γ_{sample}^{CORR} and its model counterpart, γ_{risk}^{CORR}, as in equation (13). We examine three versions of γ_{risk}^{CORR}. The first version does not restrict the betas and the factor covariances, the second version allows free betas but fixes the factor covariances to be at their TSA, and the third version allows free factor covariances but fixes betas to be at their TSA. For each version and the data, we report the mean, standard deviation, the correlation with γ_{sample}^{CORR}, the t-dan test from Bunzel and Vogelsang (2005), and the t-ps test from Vogelsang (1998). The 5% critical value (two sided) for t-dan is 2.052, and for t-ps it is 2.152. The sample period is January 1980–December 2005.

		γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA
Factor cov	γ_{sample}^{CORR}	Free	TSA	Free
Panel A: Country-Industry Portfolio Correlations				
Mean	0.366	0.370	0.514	0.447
SD	0.106	0.106	0.228	0.099
Correl(.,data)	100%	100%	−9%	91%
b-dan	−0.0009	−0.0010	−0.0002	−0.0001
t-dan	−0.377	−0.382	−0.005	−0.056
b-ps	−0.0024	−0.0024	−0.0028	−0.0013
t-ps	−0.686	−0.684	−0.160	−0.428
Panel B: Country-Style Portfolio Correlations				
Mean	0.447	0.449	0.644	0.515
SD	0.123	0.122	0.301	0.113
Correl(.,data)	100%	100%	−5%	90%
b-dan	0.0016	0.0016	0.0018	0.0023
t-dan	0.363	0.365	0.036	0.820
b-ps	−0.0003	−0.0003	−0.0015	0.0010
t-ps	−0.052	−0.049	−0.073	0.246

potential trend behavior. For all these comovement measures, we report seven statistics: the sample average, the sample standard deviation, the correlation between the particular (restricted model or unrestricted model) measure and the data measure, and two trend coefficients with their t-statistics.

Let's start with the trend results. No t-statistic is larger than one in absolute value. Consequently, we do not find a significant time trend in correlations for the base portfolios. Given the behavior of the correlations over time displayed in Figure 1, this is not surprising. There are no trends for the restricted models with constant betas or constant factor variances either. Consequently, at least for our base set of portfolios, we do not detect evidence of significant long-run changes in comovements. We re-examine this long-term behavior for meaningful subgroups of portfolios in the next few subsections.

The table reveals that the average country-industry correlation is 0.37, but this correlation also has relatively large time-variation, as its volatility is 0.11. The model perfectly mimics this time-variation as the model correlation measure shows a 100% correlation with the sample correlation measure. When we restrict the factor covariances to be at their unconditional means, we tend to overpredict correlations. One source for this phenomenon is that variances tend to exhibit positively skewed distributions, so that the sample average variance is higher than the median. Because correlations and covariances are increasing in factor variances, this tends to bias comovements upwards.

In addition, restricting factor variance dynamics to be constant leads to a correlation measure that is negatively correlated with its sample counterpart. Time-invariant betas, on the other hand, lead to correlation measures that show a 91% correlation with the sample. This indirectly shows that factor covariance dynamics are an important driver of correlation dynamics.

The evidence for country-style portfolios is qualitatively similar.

B. Long-Run Trends in Country Correlations

Correlations are an important ingredient in the analysis of international diversification benefits and international financial market integration. Of course, correlations are not a perfect measure of either concept. Correlations can increase because of changes in discount rate correlations and changes in cash flow correlations and only the former are likely related to pure *financial* market integration. Diversification benefits, even in a mean-variance setting, depend on the covariance matrix *and* expected returns.

Nevertheless, it has long been recognized that the globalization process, both in financial and real economic terms, would lead to increased correlations across the equity returns of different countries, thus eroding potential diversification benefits. Bekaert and Harvey (2000) show that emerging markets correlations with and betas relative to world market returns increase after stock market liberalizations. An extensive empirical literature focuses on the time-variation of correlations between various country returns. One of the best known papers is Longin and Solnik (1995), who document an increase in correlation between seven major countries for the 1960–1990 period. While many of these articles use parametric volatility models to measure time-variation, our approach can be viewed as nonparametric. We simply test for a trend in the time series of sample correlations.

While reforms in a small country may cause sudden changes in correlations, differently timed reforms in the cross-section and/or the gradual nature of the globalization process itself make a trend test the most suitable test to examine permanent changes in correlations.[13] However, a priori there are also channels that would cause cross-country correlations to decrease with increased financial or trade openness. For example, trade links may cause competitive pressures and industrial specialization that lower the cash flow correlations across countries. Yet, most empirical research finds that increased trade openness increases cross-country correlations: see, for instance, Baele and Inghelbrecht (2009).

[13] If an increase in correlations is the actual alternative hypothesis, the critical value of the one-sided test should be used.

Our parametric factor model permits a useful decomposition of the results. As we argued before, return correlations across countries can increase because of increased betas with respect to common international factors, increased factor volatilities, or a decrease in idiosyncratic volatilities. With our risk model, it is straightforward to decompose the temporal evolution of correlations in these separate components. Because factor volatilities show no long-term trend, permanent changes in correlation induced by globalization must come through betas. In fact, Bekaert and Harvey (1997), Fratzscher (2002), and Baele (2005) focus on time-variation in betas directly to measure financial market integration.

Table VI contains our main empirical results. Apart from all countries, we consider the following country groupings: the G7 countries, as in Longin and Solnik (1995); Europe, which witnessed various structural changes toward financial and economic integration in the context of the European Union; and the Far East, where no regional measures were taken to promote integration but some individual countries, such as New Zealand and Japan, liberalized their capital markets. Finally, we consider correlations with European and the Far East and with all countries from the perspective of a U.S. investor.

The trend tests in Panel A reveal that only the European country group experiences a significant upward trend in correlations. The trend coefficients are positive for all groupings, but typically far from statistically significant. The other group for which the trend coefficient is large and nearly significant is the correlations between the United States and Europe. Hence, the general picture is that of an integrating North American and European world, with Asia left out for now.

Next, we examine the sources of the trends by either fixing the betas or covariances at their sample averages. We start with the United States versus Europe in Panel B. We report correlation statistics for the full sample period and for a sample starting in 1986. There are two reasons for this. First, the data for many of the smaller countries in Europe are sparse before 1986, and for Spain, Greece, and Finland, we do not have data at all before 1986. Second, the integration process in Europe really started in 1986 with the Single European Act, followed by capital control relaxations in a number of countries. It is thus perhaps not surprising that there is indeed a significant trend in the correlations between the United States and Europe, even at the two-sided 5% level, when the sample is started in 1986. However, the decomposition reveals that the trend is most apparent when betas are fixed, but the decomposition loses significance when the factor volatilities are fixed. Thus, because the magnitude of the trend coefficient is larger with fixed volatilities, even though volatility bias may play a role, time-varying betas may still be the dominant factor. It is therefore interesting to consider the regional source of this trend. Panel C shows trend results for the United States with different country groups in Europe. These country groups include the European Union (EU) countries, Core EU countries (the original European Community countries, that is, France, Italy, Belgium, the Netherlands, and Germany), and the Euro countries. There is no Non-EU group, as it only consists of Switzerland, whereas the Non-Euro

Table VI

Long-Term Movements in Country Return Correlations

We aggregate our base portfolios into country portfolios, then investigate correlation statistics for several subgroups. We also investigate bivariate correlation relative to the U.S. country return. In Panels C and D, CEU stands for Core European countries, and NCEU stands for non-Core European countries. Euro collects the countries currently part of the Euro system, and EU groups the current European Union countries. We report time-series properties for γ_{sample}^{CORR} and its model counterpart, γ_{risk}^{CORR}, as in equation (13). We examine three versions of γ_{risk}^{CORR}. The first version does not restrict the betas and the factor covariances, the second version allows free betas but fixes the factor covariances to be at their TSA, and the third version allows free factor covariances but fixes betas to be at their TSA. For each version, we report the mean, standard deviation, the correlation with γ_{sample}^{CORR}, the t-dan test from Bunzel and Vogelsang (2005), and the t-ps test from Vogelsang (1998). In Panels A and E, t-dan test statistics are reported at the 5% level; in Panels B, C, and D, we present t-dan test statistics at both the 5% and 10% level. The t-dan statistics are different at 5% and 10% because of scaling to achieve optimal size in finite sample. More details are reported in Bunzel and Vogelang (2005). The 5% critical value (two-sided) for t-dan is 2.052, and for t-ps it is 2.152. The 10% critical value (two-sided) for t-dan is 1.710, and for t-ps it is 1.720. The sample period is January 1980 to December 2005.

Panel A: Correlations

γ_{sample}^{CORR}	Mean	b-dan	t-dan	b-ps	t-ps
All countries	0.385	0.0051	1.272	0.0034	0.572
G7	0.383	0.0054	1.224	0.0034	0.524
Europe	0.558	0.0074	3.278	0.0061	2.076
Far East	0.326	0.0024	0.401	0.0002	0.023
U.S. vs. Far East	0.281	0.0020	0.719	0.0002	0.057
U.S. vs. Europe	0.394	0.0078	1.653	0.0061	0.762
U.S. vs. all other countries	0.365	0.0055	1.246	0.0037	0.514
γ_{risk}^{CORR}	Mean	b-dan	t-dan	b-ps	t-ps
All countries	0.389	0.0051	1.299	0.0034	0.586
G7	0.387	0.0054	1.247	0.0035	0.536
Europe	0.617	0.0052	2.019	0.0037	1.077
Far East	0.364	0.0033	0.452	0.0011	0.115
U.S. vs. Far East	0.281	0.0020	0.733	0.0002	0.063
U.S. vs. Europe	0.395	0.0077	1.666	0.0061	0.764
U.S. vs. all other countries	0.365	0.0055	1.240	0.0037	0.512

(*continued*)

countries also include the U.K., Denmark, Sweden, and Norway. Focusing on the 1986–2005 sample, all subgroups seem to display trending behavior, but EU membership, being part of the Euro group, and even more so, being in the core EU countries increases the trend coefficient and its significance.

One of the most interesting results in Panel A is the increase in correlations within Europe. Unfortunately, the risk model appears to work less well for Europe than for other countries and seems to miss part of the trend apparent in the data. Further examination of this issue reveals that this is primarily

Table VI—*Continued*

Panel B: U.S. vs. Europe				
Beta Factor cov	γ_{sample}^{CORR}	γ_{risk}^{CORR} Free Free	γ_{risk}^{CORR} Free TSA	γ_{risk}^{CORR} TSA Free
		1980–2005		
Mean	0.394	0.395	0.529	0.473
SD	0.221	0.222	0.356	0.167
Correl(.,data)	100%	100%	28%	84%
b-dan	0.0078	0.0077	0.0076	0.0063
t-dan (5%)	1.653	1.666	0.317	4.330
t-dan (10%)	2.093	2.106	0.514	4.685
b-ps	0.0061	0.0061	0.0025	0.0058
t-ps	0.762	0.764	0.174	2.659
		1986–2005		
Mean	0.413	0.414	0.521	0.501
SD	0.235	0.235	0.385	0.161
Correl(.,data)	100%	100%	34%	86%
b-dan	0.0128	0.0128	0.0169	0.0078
t-dan (5%)	2.090	2.141	0.628	3.725
t-dan (10%)	2.623	2.682	0.960	4.088
b-ps	0.0127	0.0127	0.0110	0.0078
t-ps	1.585	1.620	0.715	2.740

Panel C: γ_{sample}^{CORR} for the U.S. with Different European Areas					
European Areas	CEU	NCEU	Euro	NEuro	EU
		1980–2005			
Mean	0.393	0.393	0.383	0.401	0.398
SD	0.241	0.224	0.229	0.234	0.223
b-dan	0.0099	0.0063	0.0091	0.0067	0.0080
t-dan (5%)	1.650	1.607	1.685	1.643	1.701
t-dan (10%)	2.231	1.893	2.239	1.939	2.152
b-ps	0.0080	0.0048	0.0074	0.0052	0.0063
t-ps	0.830	0.745	0.844	0.781	0.788
		1986–2005			
Mean	0.418	0.409	0.405	0.419	0.418
SD	0.257	0.232	0.244	0.244	0.237
b-dan	0.0157	0.0104	0.0146	0.0110	0.0130
t-dan (5%)	2.786	1.708	2.836	1.726	2.226
t-dan (10%)	3.484	2.068	3.493	2.082	2.761
b-ps	0.0156	0.0103	0.0147	0.0109	0.0130
t-ps	2.009	1.361	2.101	1.366	1.660

(*continued*)

due to the first part of the sample, where the factor models overestimate the correlations. Therefore, to discuss the decomposition in Panel D, we focus on the 1986–2005 period. The result is analogous to what we found for the U.S.–Europe correlations. There is a nearly significant trend when betas are fixed

Table VI—*Continued*

Panel D: European Countries

Beta Factor cov	γ_{sample}^{CORR}	γ_{risk}^{CORR} Free Free	γ_{risk}^{CORR} Free TSA	γ_{risk}^{CORR} TSA Free
		1980–2005		
Mean	0.558	0.617	0.901	0.719
SD	0.024	0.019	0.082	0.015
Correl(.,data)	100%	98%	31%	81%
b-dan	0.0074	0.0052	0.0189	0.0025
t-dan (5%)	3.278	2.019	0.162	0.461
t-dan (10%)	3.746	2.473	0.356	0.711
b-ps	0.0061	0.0037	0.0117	0.0014
t-ps	2.076	1.077	0.313	0.233
		1986–2005		
Mean	0.580	0.628	0.963	0.715
SD	0.177	0.145	0.612	0.108
Correl(.,data)	100%	99%	23%	91%
b-dan	0.0109	0.0085	0.0254	0.0060
t-dan (5%)	3.928	3.138	0.028	1.673
t-dan (10%)	4.423	3.617	0.096	2.250
b-ps	0.0099	0.0073	0.0138	0.0053
t-ps	2.985	2.118	0.083	1.289

Panel E: γ_{sample}^{CORR} Cross-Correlations within Europe

European Areas	CEU NCEU	EURO NEURO	CEU	NCEU	EURO	NEURO	EU
Mean	0.574	0.567	0.668	0.530	0.626	0.553	0.575
SD	0.191	0.188	0.181	0.157	0.158	0.177	0.185
b-dan	0.0118	0.0114	0.0112	0.0073	0.0094	0.0089	0.0116
t-dan	4.786	4.677	0.428	3.273	1.228	3.333	4.566
b-ps	0.0110	0.0106	0.0095	0.0059	0.0078	0.0076	0.0108
t-ps	3.882	3.875	0.560	2.193	1.043	2.136	3.644

at their sample means, suggesting the presence of volatility bias. However, the trend coefficients are much larger (but noisy) when the factor volatilities are fixed, suggesting that global and/or regional betas increase. This confirms the results in Baele (2005), suggesting that the increase in correlations may well be permanent. Interestingly, in terms of statistical significance and the magnitude of the trend coefficient, it is the cross-correlations between Core EU and non-Core EU countries and between Euro and non-Euro countries that contribute the most. The trends within Core EU and Euro countries, while large, are not statistically significant.

This suggests that pure EU-driven regional integration may not be the main force behind the trend in correlations. Because the risk model incorporates both global and regional factors, we can investigate whether it is general globalization (global betas) or regional integration within the European Union (regional betas) that caused the trend in European correlations. In unreported results, we find that by fixing only local betas, the correlation of the restricted model measure with the data is still as high as 0.98 with a positive and significant trend, while by fixing only global betas, the correlation drops to 0.81 and the trend significance disappears. This analysis suggests that the global betas account for the significant trend in the unrestricted model. This is somewhat surprising as the European structural changes were mostly aimed at promoting regional financial and economic integration. Nevertheless, the trend seems to start around 1986, which coincides with the abolition of capital controls in a number of major countries in Europe, such as France and Italy, which may have simply jump-started a global integration process within Europe.

C. The Country-Industry Debate

The country-industry debate has clear implications for stock return comovements. For example, one obvious interpretation of the potentially growing relative importance of industry versus country factors is that globalization increased country return correlations while causing more distinct pricing of industry-specific factors, lowering the correlations between industry portfolios. Because the number of countries (23) and industries (26) that we consider is about the same, aggregating our data into either country or industry portfolios leads to equally well-diversified portfolios. Hence, country and industry return correlations can be meaningfully compared.

Table VII contains the empirical results. The left-hand side panel of Panel A aggregates the country-industry portfolios into 26 industry portfolios. The average correlation between industries is 0.63, which is substantially higher than the average correlation between countries. Nevertheless, there is absolutely no evidence of a trend in industry return correlations, with the trend coefficient either zero or slightly negative. The model decomposition reveals no permanent changes in betas of industry portfolios with respect to the risk factors. The right-hand side panel of Panel A reports the results without the TMT industries, showing similar implications.

Panel B produces statistics for the difference between country and industry portfolio return correlations. The time-variation in this statistic permits a direct test of the assertions in the recent literature regarding the relative importance of the industry versus country factors. While the trend coefficient is positive, it is by no means significantly different from zero. The decomposition does not offer conclusive evidence on the source of the positive coefficient. Again, excluding the TMT sector does not alter these conclusions. We conclude that there simply is no trend and the Heston–Rouwenhorst conclusions continue to hold: Country return correlations are lower than industry return correlations and country factors dominate industry factors. Globalization has not yet changed this fact.

Table VII

The Country-Industry Debate

We aggregate the base portfolios into either countries or industries. We report time-series properties for γ_{sample}^{CORR} and its model counterpart, γ_{risk}^{CORR}, as in equation (13). We examine three versions of γ_{risk}^{CORR}. The first version does not restrict the betas and the factor covariances, the second version allows free betas but fixes the factor covariances to be at their TSA, and the third version allows free factor covariances but fixes betas to be at their TSA. For each version, we report the mean, standard deviation, the correlation with γ_{sample}^{CORR}, the t-dan test from Bunzel and Vogelsang (2005), and the t-ps test from Vogelsang (1998). The 5% critical value (two-sided) for t-dan is 2.052, and for t-ps it is 2.152. The 10% critical value (two-sided) for t-dan is 1.710, and for t-ps it is 1.720. The sample period is January 1980 to December 2005.

		γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA
Factor Cov	γ_{sample}^{CORR}	Free	TSA	Free
Panel A: Industry Portfolio Correlations				
With TMT industries				
Mean	0.630	0.639	0.957	0.716
SD	0.116	0.114	0.474	0.083
Correl(.,data)	100%	100%	−3%	88%
b-dan	0.0000	0.0000	0.0016	0.0009
t-dan	−0.019	0.012	0.005	0.787
b-ps	−0.0005	−0.0005	0.0013	0.0008
t-ps	−0.246	−0.220	0.012	0.483
Without TMT industries				
Mean	0.638	0.645	0.978	0.723
SD	0.118	0.118	0.477	0.084
Correl(.,data)	100%	100%	−3%	88%
b-dan	−0.0001	−0.0003	0.0017	0.0010
t-dan	−0.076	−0.147	0.006	0.774
b-ps	−0.0005	−0.0007	0.0019	0.0009
t-ps	−0.211	−0.278	0.018	0.508
Panel B: Country Portfolio Correlation γ – Industry Portfolio Correlation γ for Full Sample				
With TMT industries				
Mean	−0.245	−0.250	−0.400	−0.245
SD	0.142	0.141	0.295	0.119
Correl(.,data)	100%	100%	75%	88%
b-dan	0.0051	0.0051	0.0044	0.0040
t-dan	0.090	0.110	0.035	0.109
b-ps	0.0039	0.0039	0.0017	0.0029
t-ps	0.121	0.136	0.026	0.120
Without TMT industries				
Mean	−0.253	−0.256	−0.422	−0.252
SD	0.148	0.151	0.307	0.121
Correl(.,data)	100%	100%	75%	88%
b-dan	0.0052	0.0054	0.0043	0.0040
t-dan	0.083	0.091	0.041	0.082
b-ps	0.0039	0.0041	0.0011	0.0028
t-ps	0.110	0.120	0.019	0.098

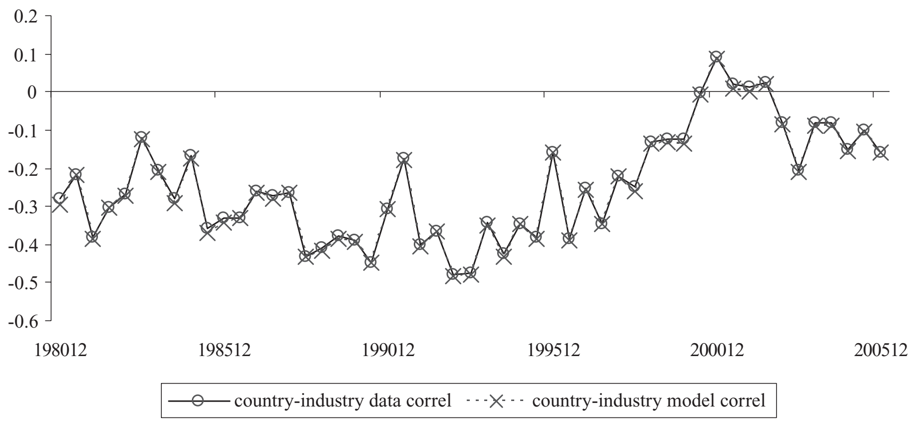
(*continued*)

Table VII—*Continued*

Beta Factor Cov	γ_{sample}^{CORR}	γ_{risk}^{CORR} Free Free	γ_{risk}^{CORR} Free TSA	γ_{risk}^{CORR} TSA Free
Panel C: Country Portfolio Correlation γ – Industry Portfolio Correlation γ for 1991–2000				
With TMT industries				
Mean	−0.289	−0.294	−0.564	−0.281
SD	0.230	0.228	0.587	0.197
Correl(.,data)	100%	100%	80%	91%
b-dan	0.0220	0.0217	0.0456	0.0178
t-dan	2.136	2.217	0.061	0.456
b-ps	0.0197	0.0194	0.0399	0.0162
t-ps	2.290	2.378	0.154	0.975
Without TMT industries				
Mean	−0.300	−0.302	−0.598	−0.288
SD	0.249	0.254	0.609	0.209
Correl(.,data)	100%	100%	80%	91%
b-dan	0.0240	0.0243	0.0473	0.0189
t-dan	1.739	1.658	0.061	0.325
b-ps	0.0213	0.0214	0.0423	0.0168
t-ps	1.915	1.878	0.158	0.749

Why do previous articles produce different results? Recall that most articles in the literature use the Heston–Rouwenhorst model with time-invariant unit betas. However, our decomposition reveals that this is not likely to drive the results. Figure 2 (Panel A) graphs the correlation difference statistic and shows the main reason for the disparate results. Most articles focus on a short sample starting in the early 1990s and ending before 2000. During this period, there was a marked increase in the correlation difference, and it became briefly positive during 2000. To show how such a short sample affects inference, we report our trend test for the 1991–2000 period in Panel C of Table VII. For the short period, we do find a positive and significant trend. We also investigate whether the TMT sector played an important role during this period by excluding the TMT sector from the industry portfolios. The right-hand side panel shows that excluding the sector does not remove the positive trend, but it does reduce its statistical significance somewhat. The decomposition shows mixed results regarding the source of the short-term trend. On the one hand, keeping the factor covariance matrix fixed still results in a rather large but extremely noisy positive trend coefficient. Yet, the trend's statistical significance is more likely due to the time-variation in factor volatilities. While the coefficients are not statistically significantly different from zero when betas are fixed to be constant over time, the t-statistics are much higher than in the time-varying beta case. It is well known that factor volatilities were much higher at the end of this small sample than they were in the beginning of this sample. Baele and Inghelbrecht (2009), using a very different methodology, reach similar conclusions.

Panel A: Country Portfolios Minus Industry Portfolios



Panel B: Style Small Portfolios Minus Style Big Portfolios

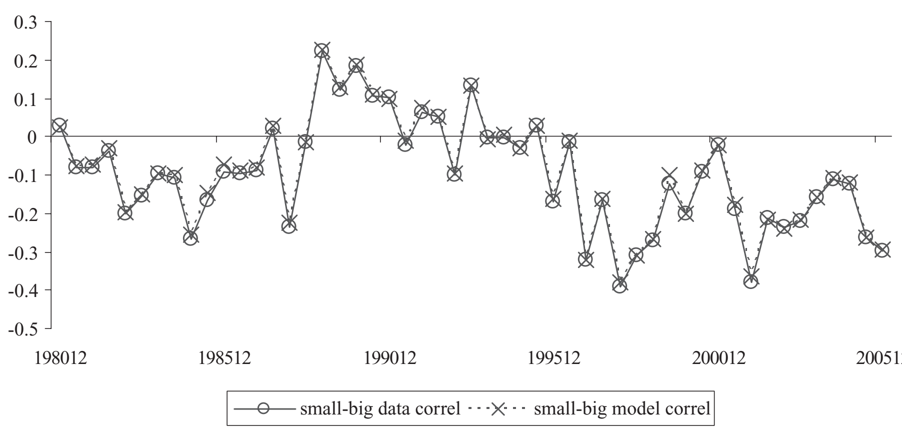
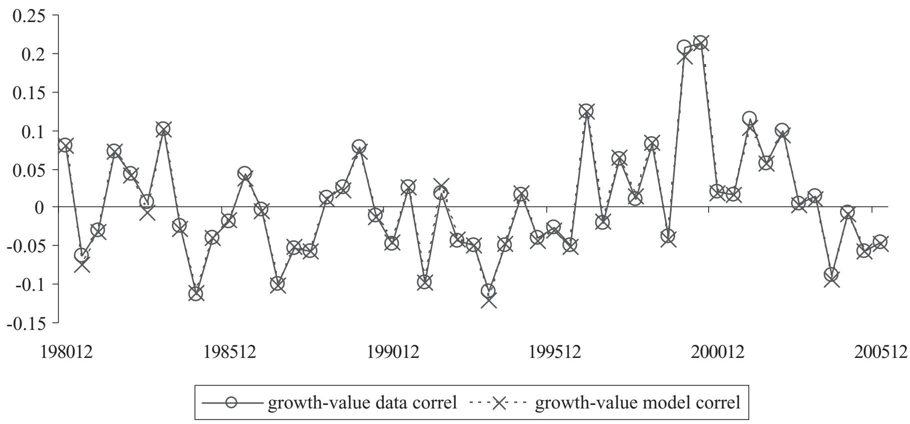


Figure 2. Time-series of portfolio correlation differences. The figure graphs the difference between two γ_{sample}^{CORR}'s (or γ_{risk}^{CORR}'s) computed using different portfolios. See equation (13) for the definition of γ_{sample}^{CORR} and γ_{risk}^{CORR}. The sample period is January 1980–December 2005.

While they find a relative change in the importance of country versus industry factors, they also show that extant studies have exaggerated the change. They attribute part of the bias to the assumption of unit betas in most studies, which misses the rather dramatic rise in the cross-sectional variation of betas toward the end of the 1990s.

D. Styles and International Return Correlations

Kang and Stulz (1997) show that international investors in Japanese stocks buy large, well-known stocks. If this investor behavior is reflected in pricing, Panel C: Style Growth Portfolios Minus Style Value Portfolios



Panel D: Style Large Growth Portfolios Minus Style Small Value Portfolios

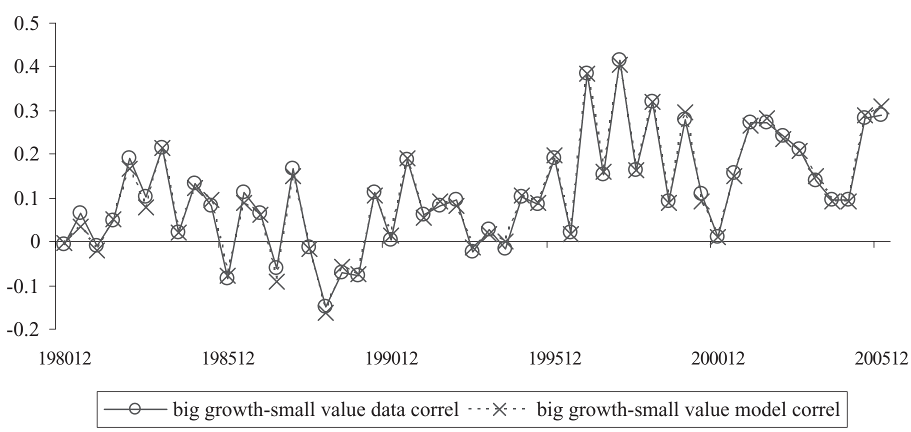


Figure 2. Continued

it is conceivable that correlations of large stock returns across countries are larger than those of small stocks. It is also possible that globalization has increased correlations of large stocks across countries (through common exposure to world demand shocks, for instance) while correlations for small stocks remain relatively low. Our methodology allows simple tests of this conjecture. In addition, we examine if there is a systematic difference between growth and value stocks in terms of international return correlations. The results are reported in Table VIII. Panel A demonstrates that the correlations among small stocks are indeed lower than those among large stocks, by about 0.05. Panel B of Figure 2 shows that the difference in correlations has changed signs a few times and was actually positive in the early 1990s. The estimated trend coefficient is negative but not significant. Panel B of Table VIII shows that the correlation among growth and value stocks is about the same at 0.36. However, the trend coefficient for the correlation difference, while not statistically significantly different from zero, is positive. The decomposition shows that this is primarily driven by changes in betas. Panel C of Figure 2 confirms that the correlations among growth stocks have become relatively larger, compared to value stock correlations during the 1990s. However, the differential has since reversed. In Panel C of Table VIII, we look at the extremes: large growth firms versus small value stocks. Not only is the correlation among the former significantly larger than among the latter, the difference has increased over time. In this case, the trend coefficient is positive and significantly different from zero. Both changes in beta and factor covariances contribute to the positive trend. Panel D in Figure 2 shows that the trend starts in the late 1980s to early 1990s.

E. Contagion and Idiosyncratic Risk

Correlation dynamics are essential in the contagion literature that built up very quickly following the Mexican and Southeast Asian crises. Contagion mostly refers to excessive correlation. While it was quickly understood that merely looking at correlation changes in crisis times may be problematic (see, for instance, Forbes and Rigobon (2001)), defining "excessive" would imply that one takes a stand on a model (see, for instance, Bekaert, Harvey, and Ng (2005), Pindyck and Rotemberg (1990), and Kallberg and Pasquariello (2008)). In the context of our framework, the factor model defines the expected correlation and what is left over could be called contagion (if it is positive). Thus, our $\gamma_{idio,\tau}^{CORR}$ can be viewed as a time-varying contagion measure.[14] Within our data set and with respect to our best fitting model, we essentially do not observe any contagion. Of course, a more powerful application would be to apply our methodology to emerging markets with a sample period encompassing crises.

Our model also has implications for variances as it decomposes the sample variance for any portfolio (or firm) into explained variance and idiosyncratic variance. We define the following measures for average portfolio (or firm)-level variances:

$$\begin{aligned} \sigma_{sample,\tau}^2 &= \sum_{j=1}^{n} w_{j,\tau}\mathrm{var}_\tau(R_{j,t}) \\ &= \sum_{j=1}^{n} w_{j,\tau}\mathrm{var}_\tau(\beta_{j\tau}' F_t) + \sum_{j=1}^{n} w_{j,\tau}\mathrm{var}_\tau(\epsilon_{j,t}) \\ &= \sigma_{risk,\tau}^2 + \sigma_{idio,\tau}^2, \end{aligned} \tag{15}$$

where n is the number of portfolios (or firms).

Campbell et al. (2001) suggest the existence of a trend in firm-specific variances. When we conduct this decomposition for our country-industry and

[14] For this application, using the APT is less desirable as one of the factors may be a "contagion" factor.

Table VIII

Long-Term Movements in Style Return Correlations

We investigate correlations in several style subgroups (small, large, value, growth) of the base portfolios. We report time-series properties for γ_{sample}^{CORR} and its model counterpart, γ_{risk}^{CORR}, as in equation (13). We examine three versions of γ_{risk}^{CORR}. The first version does not restrict the betas and the factor covariances, the second version allows free betas but fixes the factor covariances to be at their TSA, and the third version allows free factor covariances but fixes betas to be at their TSA. For each version, we report the mean, standard deviation, the correlation with γ_{sample}^{CORR}, the t-dan test from Bunzel and Vogelsang (2005), and the t-ps test from Vogelsang (1998). The 5% critical value (two-sided) for t-dan is 2.052, and for t-ps it is 2.152. The 10% critical value (two-sided) for t-dan is 1.710, and for t-ps it is 1.720. The sample period is January 1980 to December 2005.

				γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta	Small	Big	Small – Big	Free	Free	TSA
Factor cov	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	Free	TSA	Free
Panel A: Style Small versus Style Big						
Mean	0.357	0.457	−0.100	−0.095	−0.006	−0.078
SD	0.120	0.129	0.141	0.140	0.314	0.113
Correl(.,data)	100%	100%	100%	100%	60%	87%
b-dan	−0.0023	0.0015	−0.0038	−0.0038	−0.0085	−0.0037
t-dan	−0.093	0.324	−0.302	−0.322	−0.626	−0.669
b-ps	−0.0034	−0.0005	−0.0029	−0.0030	−0.0058	−0.0033
t-ps	−0.277	−0.080	−0.234	−0.247	−0.360	−0.540
				γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta	Growth	Value	Growth – Value	Free	Free	TSA
Factor cov	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	Free	TSA	Free
Panel B: Style Growth versus Style Value						
Mean	0.364	0.359	0.005	0.003	0.033	0.021
SD	0.146	0.130	0.071	0.071	0.183	0.077
Correl(.,data)	100%	100%	100%	100%	−10%	64%
b-dan	0.0035	0.0027	0.0008	0.0008	0.0042	−0.0007
t-dan	0.760	0.777	0.362	0.385	0.858	−0.408
b-ps	0.0020	0.0008	0.0011	0.0012	0.0020	−0.0005
t-ps	0.309	0.199	0.481	0.525	0.483	−0.217
			Big Growth –	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta	Big Growth	Small Value	Small value	Free	Free	TSA
Factor cov	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	Free	TSA	Free
Panel C: Style Big Growth Portfolio γ – Style Small Value Portfolio γ						
Mean	0.345	0.235	0.111	0.109	0.098	0.108
SD	0.157	0.110	0.122	0.124	0.264	0.098
Correl(.,data)	100%	100%	100%	100%	48%	70%
b-dan	0.0049	0.0008	0.0041	0.0044	0.0094	0.0024
t-dan	1.184	0.083	2.156	2.304	0.997	1.429
b-ps	0.0035	−0.0005	0.0040	0.0043	0.0073	0.0022
t-ps	0.630	−0.063	1.424	1.573	1.036	1.026

country-style portfolios, we find no evidence of a trend. Of course, our portfolios are well diversified and the idiosyncratic component does not constitute firm-level idiosyncratic variance, which was the focus of Campbell et al. (2001). In a follow-up paper, Bekaert, Hodrick, and Zhang (2009), we revisit this issue with firm-level data.

V. Conclusions

In this article, we adopt a simple linear factor model to capture international asset return comovements. The factor structure and the risk loadings on the factors are allowed to change every half year, so the model is general enough to capture time-varying market integration and to allow for risk sources other than the market.

We use country-industry and country-style portfolios as benchmarks, and we find that an APT model accommodating global and local factors best fits the covariance structure. However, a factor model that embeds both global and regional Fama–French (1998) factors comes pretty close in performance. The standard Heston–Rouwenhorst (1994) dummy variable model does not fit stock return comovements very well, and we demonstrate that the unit beta assumption it implicitly makes is quite damaging.

We use time-varying correlation measures and the factor model to re-examine several salient issues in the international finance literature. First, aggregating to country portfolios, we find little evidence of a trend in country return correlations, except within Europe. Even there, we cannot ascribe the risk in comovements with much confidence to an increase in betas with respect to the factors, which would make it more likely that the increase is permanent. It also appears that the integration of Europe within global markets is a more important driver of the permanent correlation changes than is regional integration. Consistent with this finding, we also observe weaker evidence of a trend in the correlations between the U.S. and European countries.

Second, by comparing within-country and within-industry stock return comovements, we re-examine the country-industry debate from a novel perspective. We demonstrate that the increasing relative importance of industry factors appears to have been temporary. In all, the globalization process has not yet led to large, permanent changes in the correlation structure across international stocks. It is possible that a more detailed analysis of the international dimensions (such as foreign sales, used in Diermeier and Solnik (2001) and Brooks and Del Negro (2002)) lead to different conclusions. Together, both of our main findings point toward the continuing importance of country-specific factors, suggesting that the benefits of international diversification have persisted despite globalization.

However, this does not necessarily imply that globalization has not affected international stock prices. Eun and Lee (2005) document convergence in "the risk-return distance" among 17 international stock markets, whereas Bekaert et al. (2009) document a downward trend in valuation differentials. To reconcile the different findings, a full decomposition of the effects of globalization on interest rates, equity premiums, and cash flows is necessary, which we leave to future research.

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