
**An Exploration of International Stock Return Comovement
And Portfolio Diversification**

by

Yue Mi

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Abstract

This paper addresses the issue of international portfolio diversification by examining the question whether there is a significant and persistent upward trend in international stock return comovements. We use country-style portfolios as base portfolios, and establish linear factor models to capture both the time-varying factor structures and time-varying factor loadings. We use data for the period from 1981 to 2001. Our tests indicate that the following conclusions can be made. First, there is no evidence for an upward trend of international stock return comovements. Second, there is a significant upward trend of stock return comovements only within the European countries. Third, large growth stocks are more correlated across countries than small value stocks and the difference increases after the year of 2000. All of our conclusions point toward the continuing benefits of international diversification despite of the process of globalization.

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Dedication

To my parents and Rui Hu

1. Introduction

The last decades have witnessed a rather dramatic increase in both real and financial globalization. At regional level, market integration has been strengthened through the formation of free-trade zones or currency unions, among which the adoption of Euro is a most visible example. This integration process may lead to increased correlations across the equity returns of different countries within the region, thus eroding potential diversification benefits. On the other hand, investors, especially in developed markets, now hardly face any direct or indirect barriers to international investment, and should be fully able to reap larger benefits of international portfolio diversifications. Therefore, one natural question to ask is: Is there a significant and permanent higher cross-country comovement now than used to be, such that international diversification is less favorable nowadays?

This study attempts to answer this question and is motivated by three issues. First, the analysis of the factor models is interesting on its own right. We would like to know how we should price international assets before we test the trend in comovements among different markets. Surprisingly, much of the literature on international stock return comovement imposes strong restrictions of constant, unit factor loadings with respect to a large number of country and industry factors, as in the Heston and Rouwenhorst (1994) model. We will loosen the restriction by allowing maximal flexibility in the modeling of factor loadings.

Second, a large amount of literature¹ has documented that equity market correlations tend to rise considerably when markets become increasingly economically and financially integrated, hereby reducing the potential benefits of international diversification. One example is Bekaert and Harvey (2000), which shows that correlations of emerging

¹ See for example, Longin and Solnik (1995), Goetzmann, Li and Rouwenhorst, (2005), and Bekaert, Hodrick, and Zhang (2009), and the references therein.

markets with world market returns increase after stock market liberalizations. Some other empirical literature focuses on the time-varying correlations between various country returns. For instance, Longin and Solnik (1995) document an increase in correlation between seven major countries for the period of 1960 to 1990.

Third, Kang and Stulz (1997) show that international investors tend to buy large and well known stocks in foreign stock markets. If this investor behavior is reflected in pricing, it is conceivable that correlations of large stock returns across countries are larger than those of small stocks, and correlations of growth stock returns are larger than those of value 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. It is also interesting to examine whether there is a systematic difference between growth and value stocks in terms of international return correlations.

Motivated by these issues, we study the comovements between the returns on country-style portfolios for nine countries and nine styles for the period of 1981 to 2010. During this period, markets have become more integrated at the world level through increasing international capital flows and international trade. Also, interregional cooperation has likely integrated stock markets at a regional level. These developments include the North American Free Trade Agreement (NAFTA), the introduction of the Eurozone, and the market liberalization in Asian countries. To test whether these developments have led to permanent changes in stock return comovements, the methodology of Vogelsang (1998) and Bunzel and Vogelsang (2005) for the trend test will be adopted.

For the trend test of comovement, we first investigate correlations implied by linear risk-based models with time-varying factor exposures (betas) and time-varying volatilities, which capture the facts that the degree of market integration is changing over time. 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. We also allow for maximal flexibility in the selection of the factor models 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 French three-factor model (FFM), we also consider an arbitrage pricing theory (APT) model, where the identity of the important systematic factors may change over time.

Our first conclusion is that the APT model decomposed in both global and regional factors best fits the pattern of international stock markets. A Fama–French (1993, 1996 and 1998) type model with global and regional factors is chosen as the second best model. Second, by examining time trends in country return correlations, we find a significant upward trend for stock return correlations within Europe for the period of 1991 to 2010. There is no significant evidence that the stock markets in other regions are more integrated within the sample period. Third, Large, growth firms are more correlated than small, value firms in international stock markets.

The paper is organized as follows. Section 1 introduces the data. Section 2 discusses the various factor models we consider. Section 3 chooses the best model for comovements. Section 4 provides the trend test of international stock return comovements. Section 5 presents some concluding remarks.

2. Data

We study weekly portfolio returns from nine developed markets, including the G7 countries, HK and Australia. 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 excess returns are calculated by subtracting the U.S. weekly T-bill rate, which is obtained from the Federal Reserve Economic Data. We have taken and processed the stock return data for the above nine countries from the

online database DataStream. The sample period is January 1981 to December 2010, yielding 1,560 weekly observations. The data processing and the implementation of our statistical tests have been performed by using Matlab.

Table 1 provides summary statistics for our stock return data and other data across countries. We provide time-series means for the average of firms return, average firm size, average Book-to-Market ratio and average numbers of firms. There is moderate variation in firm characteristics across countries. For instance, the average firm size ranges from \$535 million in Australia to \$3609 million in Germany, while the average firm size for the United States is \$862 million, which could be caused by the fact that U.S. stock exchanges may provide a larger coverage for small stocks. Also U.S. stocks tend to have the lowest Book-to-Market ratios (0.75), whereas Italian stocks have the highest average Book-to-Market ratios (1.62). Note that the average numbers of stocks in Germany and the U.S. dwarf the number of firms in the remaining markets.

Our basic assets are value-weighted country-style portfolio returns. The style of a portfolio, value versus growth or small versus big, is a main investing principle in the asset management industry (see Fama and French (1993, 1996 and 1998)). The behavioral finance literature also stresses the potential importance of style classification for stock return comovements. Hence, we sort firms into different styles according to their size (market capitalization) and their book-to-market (BM) ratio. The country-style portfolios are formed with the following procedure. Every year, we sort firms within each country into three groups of similar size and three book-to-market groups, with firm size and book-to-market calculated at the end of the last one-year period. The double sorting forms nine portfolios using the intersections of the size groups and the BM groups. The style portfolio level returns are the value-weighted returns of firms in the portfolio. All the portfolios have at least five stocks. Besides the global stock market containing all the nine countries, three regional markets are also defined: North America (US and Canada), Europe (UK, Germany, France and Italy) and Asia (Japan, Hong Kong and Australia).

Table 1
Summary Statistics for Country Portfolios

All numbers reported are time-series averages for the relevant statistics. The sample period is January 1981—December 2010 (30 years). The country portfolios are based on exchanges (e.g. NYSE, AMEX and NASDAQ for USA). All the returns are denominated in U.S. dollars. All the data for equities are downloaded from DataStream, and weekly U.S. Treasury bill rate is obtained from Federal Reserve Economic Data. We segregate the countries into three region groups: North America (U.S. and Canada), Europe (UK, Germany, France and Italy) and Asia (Japan, Hong Kong and Australia).

Country	Exchange	Average Firm Returns (%)	Average Firm Size (\$ mil)	Average Firm B/M	Average Number of Firms
United States	NYSE, AMEX, NASDAQ	19.56	862	0.75	2009
Canada	Toronto	13.49	753	1.35	713
United Kingdom	London	14.70	2122	0.92	1566
Germany	Frankfurt	17.12	3609	1.10	2943
France	Paris	12.19	3360	1.15	628
Italy	Milan	12.99	2100	1.62	262
Japan	Tokyo	20.01	1950	0.88	1592
Hong Kong	Hong Kong	14.69	1193	1.61	468
Australia	Australia	11.45	535	0.90	664

3. Models and Empirical Design

We start with proposing a linear factor model as the general modeling framework, which is later specified into three different models.

3.1. General Model:

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

$$R_{j,t} = E(R_{j,t}) + (\beta_{j,t}^{glo})' F_t^{glo} + (\beta_{j,t}^{reg})' F_t^{reg} + \varepsilon_{j,t}$$

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 loading 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, F_t^{reg} is a $k^{reg} \times 1$ vector of zero-mean regional shocks at time t , and $\varepsilon_{j,t}$ is a $k^{reg} \times 1$ vector of the regression residual.

A factor is defined 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 markets. Therefore, maximal flexibility in the model with regard to both global factors and regional factors is allowed. Moreover, this general model allows for time-varying exposures to global and regional factors, in order to potentially capture full or partial world or regional market integration as well as changes in the degree of integration. We choose to use as local factors regional factors rather than country factors because Brooks and Del Negro (2005) show that within the same 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 re-estimate the models every 12 months, essentially assuming that for every week t in the τ th 12-month period, $\beta_{j,t} = \beta_{j,\tau}$ with $t=1,2,\dots,1560$, because we have 30 years of data with 52 weeks in each year.

3.2. CAPM Models

The Capital Asset Pricing Model (CAPM) use market portfolio returns as the only relevant factors:

$$R_{j,t} = E(R_{j,t}) + (\beta_{j,t}^{WMKT})WMKT_t + (\beta_{j,t}^{LMKT})LMKT_t + \varepsilon_{j,t}$$

where $R_{j,t}$ is still the excess return of country-style portfolios. The factor $WMKT_t$ is calculated as the demeaned value-weighted sum of returns on all country-style portfolios, while $LMKT_t$ models the regional factors (i.e. we have three factors for the three different regions). The regional factors are calculated in two stages: First, we compute the demeaned value-weighted sum of returns on all country-style portfolios within the region. Second, we orthogonalize this return with respect to $WMKT$ using an ordinary least square regression on $WMKT$. The error term of the regression is the region-specific $LMKT$ factor. This regression is conducted every year to allow for time-varying factor loadings. The CAPM model containing both the global factors and the regional factors is called WLCAPM. The world CAPM model (WCAPM) denotes the special case in which $\beta_{j,t}^{LMKT}$ is zero.

3.3. Fama-French Models

The world-local Fama-French model (WLFF) incorporates global and regional style factors like size and value in addition to market factors:

$$R_{j,t} = E(R_{j,t}) + (\beta_{j,t}^{WMKT})WMKT_t + (\beta_{j,t}^{WSMB})WSMB_t + (\beta_{j,t}^{WHML})WHML_t \\ + (\beta_{j,t}^{LMKT})LMKT_t + (\beta_{j,t}^{LSMB})LSMB_t + (\beta_{j,t}^{LHML})LHML_t + \varepsilon_{j,t}$$

The World Fama French model (WFF) is a reduced form of the WLFF model. It contains only the market factors, size factors and value factors calculated from the world portfolios, denoting by WFF the special case for $\beta_{j,t}^{LMKT} = \beta_{j,t}^{LSMB} = \beta_{j,t}^{LHML} = 0$. The factor $WMKT$ is constructed in the same way as in the CAPM models. The term $WSMB$ is a measure of size factors in the global market. To calculate $WSMB$, we first compute the quantity $SMB(k)$ for each country k , which is the difference between the value-weighted returns of the smallest (measured by the market value under U.S. dollar) 30% of firms and the largest 30% of firms within country k . Then the factor $WSMB$ is the demeaned value-weighted sum of the individual country $SMB(k)$ quantities. The factor $WHML$ is calculated in a similar way as the demeaned value-weighted sum of the individual country $HML(k)$ quantities using high versus low book-to-market values.

World-local Fama French model (WLFF) contains the market factors, size factors and value factors calculated from both world portfolios and regional portfolios. *LMKT* is constructed in the same way as in the previous model. The regional size factor and the regional value factor, *LSMB* and *LHML* respectively, are constructed in the same way as *LMKT*, i.e. we first compute the demeaned value-weighted sum of returns within the region. Then, we orthogonalize this return with respect to *WSMB* (*WHML*) and the error term of the regression is the new region-specific factor *LSMB* (*LHML*).

3.4. APT Models

As the previous models all assume consistent forms of systematic factors, we also consider an arbitrage pricing theory (APT) model, where the identity of the important systematic factors may change over time. 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:

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

We denote the global version of the model by WAPT, and the partial integration version of the WAPT by WLAPT, 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. The factors are built as follows: We construct the factors every year by estimating the covariance matrix of all the portfolios, and extracting the three eigenvectors with the largest three absolute eigenvalues as principal factors. By construction, the factors have zero means and unit volatility, and they are orthogonal to each other. In this way, we allow the factor structure to change yearly, implicitly accommodating time-varying risk betas. The regional components are first extracted in the same way, but we use the portfolios within each region and then orthogonalize with respect to the world components.

Particularly, let $\sum_{F,\tau} = \text{cov}_{\tau}(F_t, F_t)$, where $F_t = \{(F_t^{glo})', (F_t^{reg})'\}'$ be the factor vector covariance for the τ th year period, and let $\beta_{j,t} = \{(\beta_{j,t}^{glo})', (\beta_{j,t}^{reg})'\}'$ be a loading vector. Then for "time-varying" model, the covariance of two returns R_{j_1}, R_{j_2} can be written as:

$$\text{cov}_\tau(R_{j1}, R_{j2}) = \beta'_{j1,t} \Sigma_{F,t} \beta_{j2,t} + \text{cov}_\tau(\varepsilon_{j1}, \varepsilon_{j2})$$

If the factor model fully describes stock return comovements, the residual covariance $\text{cov}_\tau(\varepsilon_{j1}, \varepsilon_{j2})$ should be zero. In this case, the covariances between two portfolios could increase through the following two effects: an increase in the factor loadings β , or an increase in the factor covariances $\Sigma_{F,t}$. If the increase in covariance is due to increased exposure to the world market β^{glo} , as opposed to an increase in factor volatilities $\Sigma_{F,t}$, 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 increasing in betas and factor volatilities, but they are decreasing in idiosyncratic volatility. Because Schwert (1989) finds that the volatility of the market portfolio, while varying over time, shows no long-term trend, it is very important to control the level of market volatility when assessing changes in correlations.

4. Model Selection

In this section, we attempt to select the best fitting model for the sample covariance structure. We first estimate the sample covariance matrix yearly, which are denoted by $\text{cov}_{sample,\tau} = 1, 2, \dots, 30$. Given our factor model set-up, we can decompose the sample covariance into two components. The first component represents the covariance between portfolios driven by their common exposures to risk factors, and the second component represents residual or idiosyncratic comovements:

$$\text{COV}_{sample,\tau} = \text{COV}_{model,\tau} + \text{COV}_{\varepsilon,\tau}$$

The factor models only have testable implications for covariance, so we let the diagonal elements in $\text{cov}_{model,\tau}$ contain the sample variances. If the factor model is true, the common factors should explain as much as possible of the sample covariance matrix and the residual covariance components should be zero. We can define $CORR_{sample,\tau}$, $CORR_{model,\tau}$, and $CORR_{\varepsilon,\tau}$ by dividing all the components of the covariance matrix by $[\text{Var}_\tau(R_i)\text{Var}_\tau(R_j)]^{0.5}$.

To examine the performance of each model relative to the other models, we introduce the statistic *MSE* (Mean Square Error) which is the Frobenius norm of the difference

between the sample and the model correlation matrix (see Ledoit and Wolf (2003)). The quantity MSE measures the time-series mean of a weighted average of squared errors:

$$\begin{aligned}
MSE_{CORR} &= \frac{1}{30} \sum_{\tau=1}^{30} \left\{ \frac{1}{\bar{W}_{\tau}} \sum_{j_1=1}^{n_{port}} \sum_{j_2>j_1}^{n_{port}} w_{j_1,\tau} w_{j_2,\tau} [CORR_{sample,\tau}(R_{j_1,t}, R_{j_2,t}) - CORR_{model,\tau}(R_{j_1,t}, R_{j_2,t})]^2 \right\} \\
&= \frac{1}{30} \sum_{\tau=1}^{30} SE_{\tau}(\text{model}) \tag{1}
\end{aligned}$$

where t indicates weekly periods, τ indexes different one-year periods, and $\bar{W}_{\tau} = \sum_{j_1=1}^{n_{port}} \sum_{j_2>j_1}^{n_{port}} w_{j_1,\tau} w_{j_2,\tau}$ is a scalar that makes the weights add up to one, individual portfolio weights $w_{j_1,\tau}$ and $w_{j_2,\tau}$ are determined by the portfolio's market capitalization from the previous period, n_{port} is the number of the portfolios in our current work (which is 9). This statistic describes the difference between the sample and the model correlation matrix, and its square root is the root mean squared error (denoted as RMSE below) for correlations. We choose to present statistics for correlations rather than covariances for ease of interpretation, but our results for covariances are qualitatively similar.

We will determine the best fitting model in Section 3.1, while in Section 3.2 we examine how the set-up of time-varying betas affects the models' ability to match the sample covariance matrix.

4.1. Minimizing RMSE

Table 2 reports the model comparison results using MSE_{CORR} . Every cell of the matrix in panel A represents the average differences between two models on the left column and the upper row. To be more specific, we define the measure of MSE difference as

$$\begin{aligned}
diff(i, j) &= MSE(\text{model } i) - MSE(\text{model } j) \\
&= \frac{1}{30} \sum_{\tau=1}^{30} [SE(\text{model } i) - SE(\text{model } j)] \\
&= \frac{1}{30} \sum_{\tau=1}^{30} diff_{\tau}(i, j) \tag{2}
\end{aligned}$$

Table 2 panel B reports the corresponding t statistic. To take into account serial correlation in the coefficient estimates, we adjust standard errors using the Newey and West (1987) approach with four lags. Given that we only have 30 observations to construct $diff(i, j)$ for each pair of model comparison, the finite sample distribution

may not be normally distributed. Therefore we use a simple bootstrap analysis to create an empirical distribution of the t -statistic. The absolute value of the critical value of a double-sided test of 5% significant level is 2.15.

One conclusion of Table 2 is the partial integration models with regional factors better match the sample covariance structure than full integration models. The average difference between MSE of WLCAPM (model i) and MSE of WCAPM (model j) is -0.0267, which indicates WLCAPM has a lower MSE than WCAPM. The corresponding t -statistic is -3.04, which indicates that WLCAPM significantly outperforms WCAPM.

Table 2

Model Fit: Matching the Sample Portfolio Correlation Matrix

In panel A, each cell (i, j) report the average difference between MSE (model i) and MSE (model j). The MSE statistics is defined in equation (1). 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 principal factors. The models WLCAPM, WLFF, and WLAPT include both local and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. In panel B, every cell (i, j) reports the t -statistics for MSE (model i) and MSE (model j), and (*) indicates that the t -statistics is significant at the 5% level, where we use the Newey-West (1987) standard error with four legs.

Panel A: Average Difference					
Difference	Model j				
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT
WLCAPM	-0.0267				
WFF	-0.0342	-0.0075			
WLFF	-0.1053	-0.0787	-0.0711		
WAPT	-0.2061	-0.1794	-0.1719	0.1007	
WLAPT	-0.2252	-0.1985	-0.1198	-0.0198	-0.191
Panel B: t-Statistics					
t-Stat	Model j				
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT
WLCAPM	-3.04*				
WFF	-5.69*	-1.15			
WLFF	-8.25*	-7.96*	-7.15*		
WAPT	-8.78*	-8.87*	-8.39*	7.41*	
WLAPT	-10.42*	-10.77*	-10.18*	-2.19*	-5.11*

We find the same pattern between WFF and WLFF, and between WAPT and WLAPT, which indicates that overlooking region-specific factors may cause severe estimation error in international asset pricing. Even though the average difference between the MSE of WFF and MSE of WLCAPM is negative, the difference is quite close to zero and not significant, which means even including size and value factors, omitting regional factors erode the validity of the WFF model.

Second, the data indicates that comparing the different factor specifications, WLAPT is the best-fitting model. The absolute values of all t -statistics in the last row are larger than the critical value, which indicates the WLAPT significantly beats all the five other models with respect to minimizing mean squared error. We can also find that WLFF may serve as a second-best modeling selection for two reasons: Even though WLAPT performs significantly better than the WLFF model, the difference between the MSEs of the two models is relatively small and the t -statistic is slightly above the critical value. Also the WLFF model significantly beats the WAPT model, which ignores regional factors even though it allows for high flexibility of global factors. Because the WLAPT model robustly provides the best match with the sample covariance matrix, we will select the WLAPT as the benchmark model for our subsequent analysis in the next subsections. The WLFF model, as a second-best model, will be used when we need systematic factors to represent the volatilities in fundamentals.

4.2. Estimation Errors and the Role of Beta Variation

Table 3 presents the correlation $RMSE_{CORR}$ for different models under different assumptions on time-variation and cross-sectional variation in the betas. In the first column of Table 3, we start with a unit-beta world CAPM model as a benchmark. That is, we assume $\beta^{WMT} = 1$ in the WCAPM model. The unit beta model generates correlations that are on average much too low, leading to a RMSE value of 0.495.

In the second column, we set factor loadings of each model equal to the cross-sectional average beta value within each regression. 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 RMSEs of the six models are all above 88% of that of the unit beta model.

The most interesting experiment in this part is presented in the third column. We set factor loadings of each model equal to the time-series average (TSA) beta for the individual portfolios. In this way, we ignore the time-varying trend of factor loading. We conclude that if the betas are fixed at the level of time-series mean, the value of RMSE still remains high. Therefore, it is necessary to allow for both time variation and cross-sectional variation in betas, as illustrated in the last column.

Table 3

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 (2). 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 one-year period. TSA beta means that all the betas in each model are set to the time series average for each country- 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 principal 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.

	Cross-section Average Betas			TSA Betas		Free Betas	
	Unit Beta RMSE	RMSE	Percentage of Unit Beta RMSE (%)	RMSE	Percentage of Unit Beta RMSE (%)	RMSE	Percentage of Unit Beta RMSE (%)
WCAPM	0.495	0.480	97	0.463	94	0.280	57
WLCAPM		0.479	97	0.375	76	0.152	31
WFF		0.486	98	0.388	78	0.243	49
WLFF		0.483	97	0.366	74	0.104	21
WAPT		0.413	83	0.608	123	0.217	44
WLAPT		0.438	88	0.451	91	0.096	19

In the last column, we propose the unconditional model with free betas. If we allow for time-varying beta and include regional factors, the RMSE measure decreases to 0.096 for the WLAPT model and 0.104 for the WLFF model. These two models featuring regional factors miss the correlation on average only by around 0.1, which further supports our previous finding that WLAPT and WLFF are the best-fitting models.

5. Trends in Comovements

In this section, we study long-trend movements in correlations in international stock markets. We start with a discussion of the methodology of trend test and a general test in the global scope to address whether global market integration is a long and persistent trend. In second part, we consider the long-run behavior of correlations between country returns within specific regions, addressing the question of whether interregional cooperation has indeed caused regional return correlations to increase over the period of 1981 to 2010. Following Section 4.3, we further investigate the role of style as a driver of international return correlations.

5.1. Methodology and Trends in global portfolio correlations.

We first define the following comovements measures for average portfolio-level covariance $r_{sample,\tau}^{cov}$, decomposed into average portfolio-level risk covariance $r_{risk,\tau}^{cov}$ which could be explained by the factor models, and the idiosyncratic covariance $r_{idio,\tau}^{cov}$, which are portfolio-specific risks failed to be captured by the models:

$$\begin{aligned} r_{sample,\tau}^{cov} &= \frac{1}{\bar{W}_\tau} \sum_{j1=1}^{n_{port}} \sum_{j2>j1}^{n_{port}} w_{j1,\tau} w_{j2,\tau} \text{cov}_\tau(R_{j1,t}, R_{j2,t}) \\ &= \frac{1}{\bar{W}_\tau} \sum_{j1=1}^{n_{port}} \sum_{j2>j1}^{n_{port}} w_{j1,\tau} w_{j2,\tau} \text{cov}_\tau(\beta'_{j1} F_t, \beta'_{j2} F_t) + \frac{1}{\bar{W}_\tau} \sum_{j1=1}^{n_{port}} \sum_{j2>j1}^{n_{port}} w_{j1,\tau} w_{j2,\tau} \text{cov}_\tau(\varepsilon_{j1,t}, \varepsilon_{j2,t}) \\ &= r_{risk,\tau}^{cov} + r_{idio,\tau}^{cov} \end{aligned}$$

where $\bar{W}_\tau = \sum_{j1=1}^{n_{port}} \sum_{j2=1, j1 \neq j2}^{n_{port}} w_{j1,\tau} w_{j2,\tau}$ is a scalar that normalizes the sum of the weights to one. For easier interpretation, we focus on the same method of decomposition for correlations as before. That is, we consider

$$r_{sample,\tau}^{CORR} = r_{risk,\tau}^{CORR} + r_{idio,\tau}^{CORR}$$

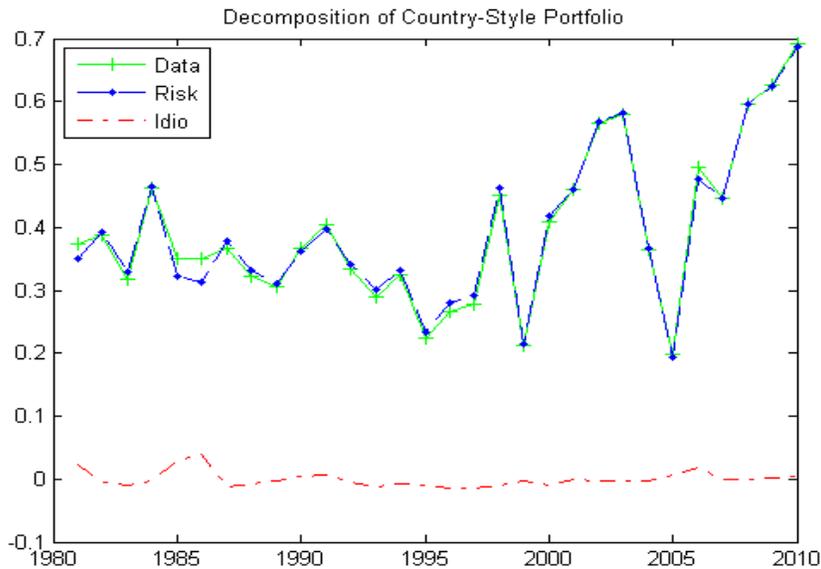
In the following section, we use the WLFF model as benchmark model for two reasons: First, it has been proved that WLFF is the second-best model compared to WLAPT models, with only slightly larger values of RMSE (0.104 compared to 0.096). Second, unlike the WLAPT model, the WLFF model allows us to disentangle the sources of the time-variance in comovements in terms of time-variation in betas and the time-variation in factor covariance. Figure 1 presents the decomposition of r_{sample}^{CORR} , r_{risk}^{CORR} , and r_{idio}^{CORR} by

the WLFF model for country-style portfolio correlations all over the world. The model closely matches the time series of average portfolio-level correlations. Reflecting this good fit, the residual correlations in Figure 1 are very close to zero.

Figure 1

Time series of Portfolio Level Correlation Measure

The data correlation and its decomposition are defined as $r_{sample,\tau}^{CORR} = r_{risk,\tau}^{CORR} + r_{idio,\tau}^{CORR}$, where “Data” refers to $r_{sample,\tau}^{CORR}$, “Risk” refers to $r_{risk,\tau}^{CORR}$ and “Idio” refers to the difference between them. The sample period is from January 1981 to December 2010.



We need to examine the questions whether correlation of our country-style portfolios displays trending behavior brought about by the process of globalization. We therefore conduct trend tests for both r_{sample}^{CORR} and r_{risk}^{CORR} . The main reason to include correlations implied both by the sample and factor model is that the best models (WLAPT and WLFF) fit the data well and help interpret the trend results in terms of their underlying sources, which could be the changes on beta and (or) the factor volatility. To formally test the significance of the time trend, we use Vogelsang’s (1998) simple linear time trend test. The benchmark model is defined to be:

$$y_t = \beta_0 + \beta_1 t + u_t,$$

where y_t is the variable of interest. In our case, it could represent both r_{sample}^{CORR} and r_{risk}^{CORR} , t is a linear time trend ($t = 1, 2, 3, \dots, 30$). We use the PS1 and the improved PSW test in Vogelsang (1998) to test $\beta_1 = 0$. The test statistic is robust up to $I(0)$ and $I(1)$ error terms. In addition, Bunzel and Vogelsang (2005) develop a test that retains the good properties of the PS1 and PSW tests, but is more powerful for small samples, which is our case. We subscript this test by “dan”, as the test uses a “Daniell kernel” to nonparametrically estimate the error variance needed in the test. In fact, tests based on this kernel have maximal validity in a wide range of kernels (see Sayginsoy (2004)).

We first apply the trend test to the country-style portfolio in the world scope. As we argued before, return correlations across countries can increase because of increased betas with respect to common international factors, increased factor volatilities, or decreased idiosyncratic volatilities. As shown in Figure 1, the idiosyncratic volatilities are small in magnitude. We mainly decompose the first two possible explanations in Table 4. We investigate the sample and model comovement measures and two alternative measures, computed by either setting the loadings or the factor covariance matrix 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). This decomposition sheds light on the source of potential trend behavior. For all these comovement measures, we report nine statistics: the sample average, the sample standard deviation, the correlation between the particular measure and the data measure, the three trend coefficients and their corresponding t -statistics.

The most prominent conclusion here is related to the trend results. As Table 5 shows, no t -statistic is larger than the critical value for the linear trend test. Consequently, we do not find a significant and persistent trend in correlations for the world base portfolios. Given the erratic behavior of the sample and model 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 the level of global portfolios, we do not detect significant long-run changes in comovements. We will re-examine this long-term behavior for regional subgroups of portfolios in the next few subsections.

Table 4

Trend in Correlations of World Base Portfolio

We report time-series properties for sample correlations and its model counterpart as defined in equation (2). Here the correlations include the country portfolios all around world. We examine three versions of model correlations. The first version does not restrict the beta and the factor covariance, the second version allows for free betas, but fixes the factor covariance to be at their TSA, and the third version allows for free factor covariance but fixes betas to be at their TAS. For each version, we report the mean, standard deviation, the t-dan test from Bunzel and Vogelsang (2005), the t-ps test from Vogelsang (1998), and t-psw test from Vogelsang (1998). The 5% critical value (two-sided) for t-dan is 2.052, for t-ps it is 2.152, and for t-psw it is 2.134. The sample period is from January 1981 to December 2010.

<i>Beta</i>	<i>Factor</i>	<i>Cov</i>	<i>Mean</i>	<i>SD</i>	<i>Correl</i>	<i>b-dan</i>	<i>t-dan</i>	<i>b-ps</i>	<i>t-ps</i>	<i>b-psw</i>	<i>t-psw</i>
		γ_{sample}^{CORR}	0.394	0.015	100%	0.0067	1.785	0.0035	0.520	0.0035	0.454
Free	Free	γ_{risk}^{CORR}	0.395	0.014	100%	0.0069	2.035	0.0040	0.762	0.0040	0.564
Free	TSA	γ_{risk}^{CORR}	0.514	0.253	-8%	0.0015	1.524	0.0027	1.042	0.0018	0.453
TSA	Free	γ_{risk}^{CORR}	0.462	0.079	94%	0.0007	1.428	0.0010	1.793	0.0013	0.367

Moreover, from the first and second rows of Table 5, we find that the WLFF model with free betas and free factor covariances stably captures the time variance of sample correlations: First, the mean of γ_{sample}^{CORR} and γ_{risk}^{CORR} are almost the same (0.394 and 0.395) with low standard deviations respectively (0.015 and 0.014). Second, the measure of free betas and free factor covariances shows a correlation of 100% with the sample correlation measure.

There are also two interesting findings about the third and fourth rows: On one hand,

when we restrict the factor covariances to be at their unconditional means, we tend to over predict correlations. This is indicated by the increased mean and standard deviations of γ_{risk}^{CORR} in the third row (0.514 and 0.253, respectively), compared with the first and second row. In addition, restricting factor variance dynamics to be constant also leads to a negative correlation with its sample counterpart. On the other hand, the model with time-invariant betas and time-varying factor covariances shows less erratic volatility, which can be seen from the fact that the standard deviation in the last row (0.079) is much lower than that in the third row (0.253). Considering both these two findings, we can argue that, at least to some extent, factor covariance dynamics may be a more dominant driver of correlation dynamics. Previous literature which fails to decompose the increasing correlation into betas and factor volatilities tends to bias comovements in upward direction.

5.2. Long-term trends in country subgroups

In the previous section, we do not find a significant and persistent trend in correlations for the world portfolios. However, it is likely that within some country groupings, the structural change of financial and economic integration reinforces stock market correlation, like in the case of the European Union. It is also likely that the similar structural change toward liberalized capital markets in Asian countries in the late 1980s promotes regional market comovements (see Bekaert and Harvey (2000)). Also Baele and Inghelbrecht (2009) find that increased trade openness increases cross-country correlations among G7 countries. To examine whether the correlations within these country groupings are significant and persistent, we apply the same trend tests to some specific country subgroups including G7, Europe, Asia and North America. Table 5 contains our main empirical results.

Table 5

Trend in Correlation of Country Group Portfolios

We aggregate our base portfolios into country subgroups, then investigate correlation statistics for each of the subgroups, and report the main results in Panel A. In Panel B, we investigate the correlation in two different time periods. Similar as before, we consider the case of free beta, i.e. do not restrict the betas and the factor covariance. We report the mean, standard deviation, the t-dan test from Bunzel and Vogelsang (2005), the t-ps test from Vogelsang (1998), and t-psw test from Vogelsang (1998). The 5% critical value (two sided) for t-dan is 2.052, for t-ps it is 2.152, and for t-psw it is 2.134. The sample period is January 1981 to December 2010.

Panel A: Correlations of different country groups								
γ_{sample}^{CORR}	Mean	SD	b-dan	t-dan	b-ps	t-ps	b-psw	t-psw
Europe	0.520	0.028	0.0071	3.833*	0.0018	1.814	0.0018	1.788
Asia	0.559	0.020	-0.0064	-1.047	-0.0075	1.381	-0.0075	1.304
North America	0.485	0.170	0.0012	0.365	0.0009	0.034	0.0009	0.017
G7	0.4001	0.015	0.0065	1.780	0.0033	0.459	0.0033	0.442
γ_{risk}^{CORR}	Mean	SD	b-dan	t-dan	b-ps	t-ps	b-psw	t-psw
Europe	0.515	0.027	0.0055	1.403	0.0015	0.976	0.0015	0.848
Asia	0.579	0.021	-0.0066	-1.568	-0.0075	1.744	-0.0075	1.655
North America	0.499	0.016	0.0007	0.236	0.001	0.085	0.001	0.007
G7	0.399	0.014	0.0068	2.073*	0.0038	0.724	0.0038	0.567
Panel B: Correlations of two different periods (Europe)								
	1981.1-2010.12		1991.1-2010.12					
	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}				
Mean	0.52	0.515	0.513	0.523				
SD	0.028	0.027	0.038	0.035				
b-dan	0.0041	0.0055	0.0176	0.0155				
t-dan	0.833	1.403	4.748*	7.057*				
b-ps	-0.0008	0.0015	0.0144	0.0122				
t-ps	0.814	0.976	2.782*	2.499*				
b-psw	-0.0008	0.0015	0.0144	0.0122				
t-psw	0.788	0.848	2.630*	2.577*				

The trend tests for sample and model correlations are shown in Panel A of Table 5. For sample correlations, only the European country group experiences a significant upward

trend in correlations, as revealed by the t-dan test. The trend coefficients for the sample correlations for North America and the G7 group are positive, but far away from being statistically significant. Surprisingly, for the Asia country group, both the sample and model comovements are insignificantly negative. To some extent, this suggests that Asian markets are more segregated than North American and European markets.

Another interesting result in Panel A is that even though there is an increase in correlations within the Europe sample group, the risk model appears to work less well for Europe than for other countries, and seems to miss parts of the trend apparent in the data. Further examination in Panel B segregates the time periods into two periods to address the issue. In the time period of 1991 to 2010, we find that there is a highly significant upward trend (with a t -statistic of 4.748 and 7.057, respectively) in both the sample and model correlation for the European group, suggesting that the increase in correlations may well be permanent after the 1990s.

5.3. Styles and International Return Correlations

As stated in the introduction, investors in foreign stocks tend to buy large and well-known stocks. If this behavior is reflected in pricing, it is possible 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 for a simple test of this conjecture. In addition, we examine the question whether there is a systematic difference between growth and value stocks in terms of international return correlations. The results are reported in Figure 2 and Table 6.

Figure 2

Time series of Portfolio Correlation Difference

Figure 2 graphs the difference between $r_{sample,\tau}^{CORR}$ and $r_{risk,\tau}^{CORR}$, computed using different portfolios. The sample period is from January 1981 to December 2010.

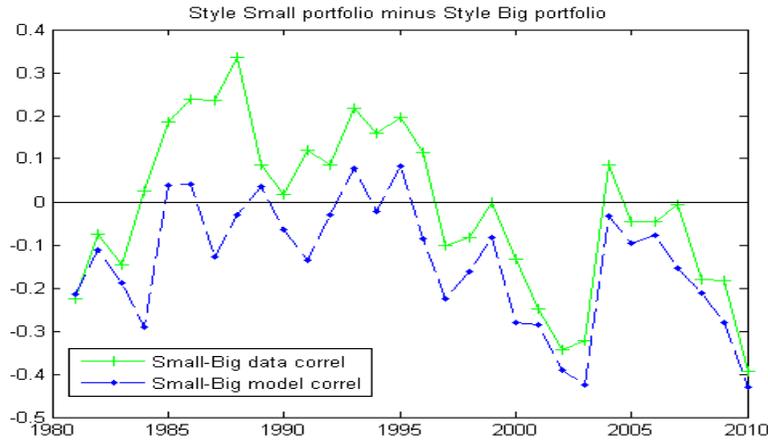


Figure 2-Panel A

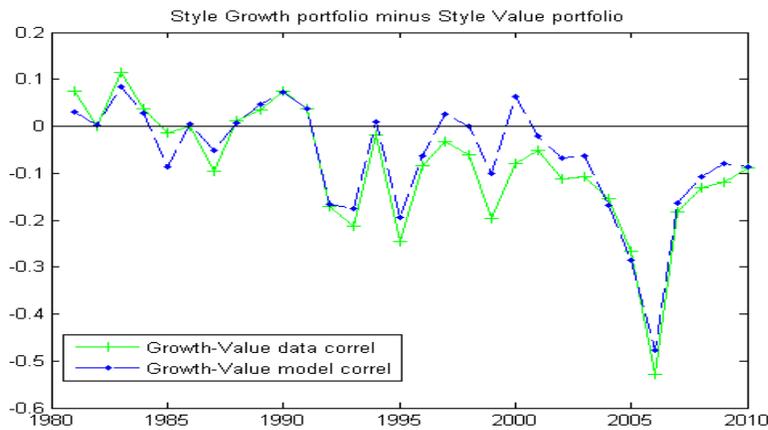


Figure 2-Panel B

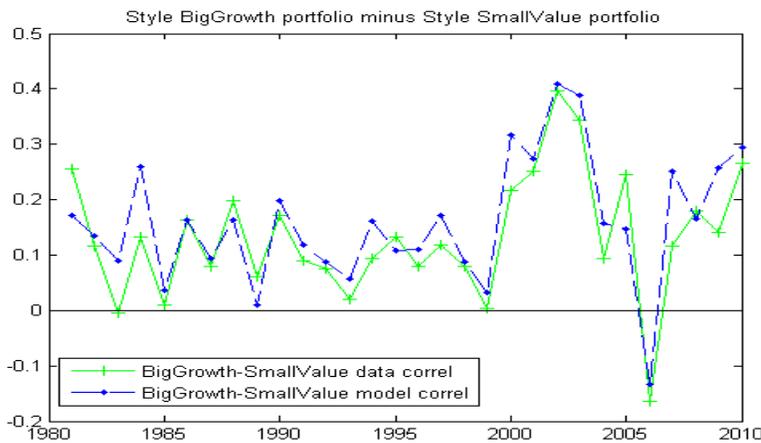


Figure 2-Panel C

Table 6
Long-Term Movements in Style Return Correlations

Panel A: Style Small versus Style Big						
Beta Factor Cov	γ_{sample}^{COR1}			γ_{risk}^{CORR}		
	Small	Big	Small-Big	Small	Big	Small-Big
Mean	0.383	0.397	-0.014	0.258	0.397	-0.139
SD	0.019	0.015	0.035	0.008	0.015	0.02
b-dan	-0.0036	0.0066	-0.0102	0.0004	0.0069	-0.0065
t-dan	-0.833	1.723	-1.63	0.142	2.024	-1.643
b-ps	-0.0058	0.0034	-0.0092	-0.0014	0.004	-0.0054
t-ps	0.959	0.444	1.006	0.178	0.74	0.846
b-psw	-0.0058	0.0034	-0.0092	-0.0014	0.004	-0.0054
t-psw	0.093	0.416	0.307	0.003	0.552	0.303

Panel B: Style Growth versus Style Value						
Beta Factor Cov	γ_{sample}^{CORR}			γ_{risk}^{CORR}		
	Growth	Value	Growth-Value	Growth	Value	Growth-Value
Mean	0.397	0.403	-0.086	0.315	0.038	-0.065
SD	0.016	0.027	0.016	0.015	0.023	0.014
b-dan	0.0063	0.0156	-0.0092	0.0062	0.0134	-0.0072
t-dan	1.618	0.612	2.356*	1.805	0.881	-3.039*
b-ps	0.0037	0.0139	-0.0103	0.0038	0.011	-0.0072
t-ps	0.432	1.091	12.503*	0.569	1	4.521*
b-psw	0.0037	0.0139	-0.0103	0.0038	0.011	-0.0072
t-psw	0.317	0.335	2.483*	0.386	0.369	2.208*

Panel C: Style Big Growth versus Style Small Value						
Beta Factor Cov	γ_{sample}^{COR1}			γ_{risk}^{CORR}		
	Big Growth	Small Value	Big Growth - Small Value	Big Growth	Small Value	Big Growth - Small Value
Mean	0.312	0.18	0.132	0.309	0.149	0.16
SD	0.017	0.013	0.012	0.015	0.087	0.013
b-dan	0.0066	0.004	0.0026	0.0065	0.0028	0.0037
t-dan	1.657	1.383	2.851*	1.869	1.156	2.683*
b-ps	0.004	0.0013	0.0027	0.0041	0.0005	0.0036
t-ps	0.483	0.091	0.834	0.653	0.025	1.313
b-psw	0.004	0.0013	0.0027	0.0041	0.0005	0.0036
t-psw	0.325	0.225	0.188	0.402	0.176	0.343

Panel A of Table 6 demonstrates that the correlations of small stocks are lower than those of large stocks, by about 0.015. Panel A of Figure 2 shows that the difference in correlations has changed signs several times and was actually positive in the period from 1985 to 1990. The estimated trend coefficient is negative but not significant. Panel B of Table 6 shows that the correlation between growth and value stocks is about the same at 0.40. However, the trend coefficient for the correlation difference, while not statistically significantly different from zero, is negative.

Panel B of Figure 2 confirms that the correlations of growth stocks have become relatively larger, compared to value stock correlations during the 1990s. However, the rate of change has reversed significantly in around 2005. In Panel C of Table 6, we look at the extremes: large growth firms versus small value stocks. Not only is the correlation of the former significantly larger than that of the latter, the difference has increased over time. In this case, the trend coefficient is positive. Panel C in Figure 2 shows that the difference is almost always positive, and there is a clear upward and then downward trend for the period of 2000 to 2005.

5.4. Contagion and Idiosyncratic Risk

Correlation dynamics are essential in the contagion literature that built up very quickly following the Mexican and Southeast Asian crises in the middle of the nineties. Contagion mostly refers to excessive correlation during a period of crisis. In the context of our framework, the factor model defines the expected correlation and what is left could be called contagion. Thus, our quantity $r_{idio,\tau}^{CORR}$ can be viewed as a measure for time-varying contagion. Within our data and our best fitting model, we decompose $r_{sample,\tau}^{CORR} = r_{risk,\tau}^{CORR} + r_{idio,\tau}^{CORR}$ for the country-style portfolio correlations of the G7 countries and the Asian countries, respectively, in Figure 3.

Figure 3

Time series of regional portfolio Correlation

The data correlation and its decomposition are defined as $r_{sample,\tau}^{CORR} = r_{risk,\tau}^{CORR} + r_{idio,\tau}^{CORR}$, where “Data” refers to $r_{sample,\tau}^{CORR}$, “Risk” refers to $r_{risk,\tau}^{CORR}$, and “Idio” refers to the difference between them. The portfolios are in the Asia and G7 group, and the sample period is from January 1981 to December 2010.

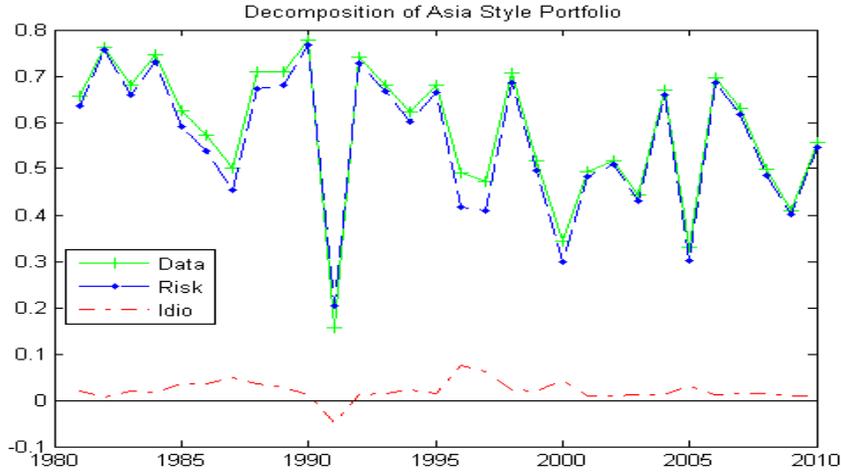


Figure 3-Panel A

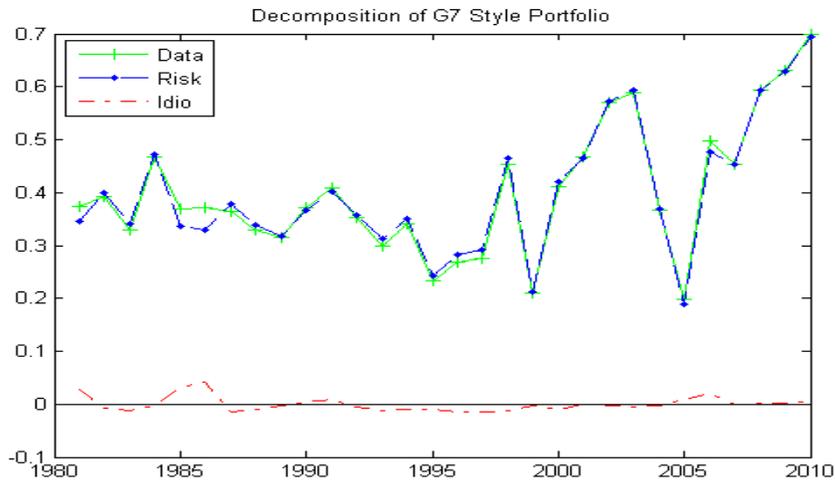


Figure 3-Panel B

As Figure 3 Panel A shows, there is an increase in $r_{idio,\tau}^{CORR}$ of Asia in the period between 1997 and 2000 (as indicated by the “Idio” line), which corresponds to the Asian Financial Crisis. But the same decomposition of G7 doesn’t show much increase in the

period from 1981 to 2010. To some extent, this feature supports the conjecture that financial contagion, measured by $r_{idio,\tau}^{CORR}$ in our framework, may exist in the period of crisis especially for emerging market such as Asia in the period from 1997 to 2000.

So far the tests for $r_{sample,\tau}^{CORR}$ and $r_{risk,\tau}^{CORR}$ fail to reveal significant trend on the global and regional level, which justifies the necessity for world diversification. And even though Figure 3 shows some trend in some specific time period for specific regions, we still find no evidence from the tests for a significant trend in $r_{idio,\tau}^{CORR}$. 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 fact, Ang *et al.* (2009) shows empirically that idiosyncratic volatility does have a negative effect on the expected return at the firm level.

6. Conclusions

In this paper, we adopt a linear factor model to evaluate the benefits of international diversification by capturing international asset return comovements. The factor structure and the risk loadings of the factors are allowed to change yearly, so that the model is general enough to capture time-varying market integration and to allow for both global and regional risk sources. Using data for country-style portfolios as benchmarks, we find that an WLAPT model accommodating global and regional factors best matches the sample portfolio correlation matrix in the sense that it minimizes the idiosyncratic correlation part which could not explained by the model itself. However, a factor model that includes both global and regional Fama-French factors performs almost as well.

We define the time-varying sample and model correlation measures and use the selected WLFF model to re-examine several important issues in international portfolio diversification. First, considering the global market and using the general trend test methodology on both sample and model correlations, we do not find a significant and persistent trend in correlations for the world base portfolios. Consequently, at the level of

global portfolios, we do not detect significant long-term changes in comovements. In addition, there are no trends for the restricted models with constant betas or constant factor variances as well, so we cannot ascribe the risk in comovement with much confidence to an increase in betas with respect to the factors, which would make it more likely that the increase is permanent.

Second, we re-examine this long-term behavior for portfolios of regional subgroups, expecting to find whether regional integration has an impact on stock return comovement. We conclude that a highly significant trend in correlation for the European countries in the period of 1991 to 2010 is corresponding to the period of political and economic integration of European countries. Third, we examine the long-term behavior for style subgroups of portfolio and find that the correlation of large-growth portfolio is significantly larger than that of small value portfolios. Therefore there is systematic difference between these two types of stocks in terms of international return correlation.

To conclude, all our main findings point to the continuing importance of country-specific factors, suggesting that the benefits of international diversification have persisted despite globalization. A possible extension of this work could focus on the excess comovement during the years of crisis and study how portfolio management changes in the face of financial contagion.

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