International Stock Return Comovements

Geert Bekaert[a,b], Robert J. Hodrick[a,b], Xiaoyan Zhang[c1]

[a] *Graduate School of Business, Columbia University, New York, NY 10027, USA*

[b] *NBER, 1050 Massachusetts Avenue, Cambridge, MA 02138, USA*

[c] *Johnson Graduate School of Management, Cornell University, Ithaca, NY 14853, USA*

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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 covariance structure of the data better than the popular Heston-Rouwenhorst (1994) model. We then establish the following stylized facts regarding stock return comovements. First, we do not find 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, temporary phenomenon.

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1. Introduction

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. Clearly, the first and second questions are related, but few articles have actually made the link explicitly. Third, the study of correlations was also given 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 article by Karolyi (2003) or Dungey, Fry, Gonzalez-Hermosillo and Martin (2005). In a domestic context, Barberis, Shleifer and Wurgler (2005) suggest that behavioral factors (for instance, a style clientele for large stocks) may induce excessive correlation between stocks and Kallberg and Pasquariello (2004) test for "contagion" in US 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 9 styles during 1980 –2005. During this period, markets may have become more integrated at a 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 NAFTA, the emergence of the Euro, and the 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 in Vogelsang (1998) and Bunzel and Vogelsang (2005).

While we apply our tests to non-parametrically 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 also help us to interpret our results better. In particular, a low-frequency but temporary change in factor volatilities may lead to spurious trends in comovement statistics, whereas increasing global betas are more indicative of a permanent change. 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 and 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 CAPM and the Fama-French (1993) model, we consider an arbitrage pricing theory (APT) model where the identity of the important systematic factors may change through 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. 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 only find a significant upward trend for stock return correlations within Europe. Third, we revisit the industry-country 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 90's, this evolution has been halted and reversed, and we find 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, we also examine the correlation between portfolios of similar styles across countries. We detect a pattern that large growth stocks are more correlated across countries than are small value stocks, and that the difference has increased over time.

The paper is organized as follows. Section 2 introduces the data. Section 3 discusses the various factor models we consider. We choose the best model for comovements in section 4. Section 5 provides the salient empirical results using country-industry and country-style portfolios. Section 6 concludes.

2. 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 non-synchronous trading around the world at higher frequencies. All returns are US dollar denominated, and we calculate excess returns by subtracting the US weekly T-bill rate, which is obtained from the CRSP riskfree file[2]. Our selection of developed countries matches the countries currently in the Morgan Stanley Developed Country Index. Data for the US are from Compustat and CRSP. Data for the other countries are from DataStream. The sample period is 1980:01 to 2005:12, yielding 1357 weekly observations.

Table 1 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[3]. We require that firms have a market capitalization of more than $ 1million. We examine the average firm annual return, the average firm size, and the average firm 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 $1538 million for Japan. The average BM is 0.71 for Japan 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 SIC. We group the 30 industries of SIC and the level 4 FTSE classifications with 40 industries into a smaller number of industries that approaches the number of countries in our sample, resulting in 26 industries. An Appendix table 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 vs. growth or small vs. big, is a main organizing principle in the US asset management industry. The behavioral finance literature has also stressed the potential importance of style classification for stock return comovements. Hence, we also sort

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

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

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 six months, we independently sort firms within each country into three size groups and three BM groups. Firm size and BM are calculated at the end of the last six-month period[4]. 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 5 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. The TMT industries (info tech, media and telecom) witnessed a tremendous increase in volatility during that period, as Brooks and Del Negro (2004) documents. This increase in volatility is also noticeable for the style portfolios, especially for the small firms. Fortunately, 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.

3. Models and Empirical Design

This section presents the various models that we estimate. We begin with a general model; then introduce different model specifications within the general model framework.

3.1. 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, $R_{j,t}$,

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

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. Because the focus in this article is on second moments, we do not further explore the implications of the factor model for expected returns.

[4]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 US firms, we take the book value that is available at the end of the last six-month period.

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 process of moving towards market integration may not be smooth. 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 factors 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. By using regional factors, we also reduce the number of factors included in each model.

To identify the time-variation in the betas and factor volatilities, we consider two approaches. First, we simply re-estimate the models every six months, essentially assuming that for every week t in the τth six-month period, $\beta_{j,t} = \beta_{j,\tau}$, with $t = 1, 2, ..., 1357$, and $\tau = 1, 2, ..., 52$, 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, but we also estimate model-implied covariances, which depend on betas and factor volatilities[5]. For the second approach, we specify

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

The interest rate is the U.S. one week T-bill rate and $\sigma_{j,\tau-1}$ represent 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 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 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 $\Sigma_{F,\tau} = cov_\tau(F_t, F_t)$ be a $(k^{glo} + k^{reg}) \times (k^{glo} + k^{reg})$ factor covariance matrix for the $\tau - th$ six-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

[5]We start the sample in January, but we also re-did our tests using a sample starting in the half year on April 1st, which yielded qualitatively similar results.

$\tau - th$ six-month period. In the first approach, the covariance of two returns, R_{j1}, R_{j2} ($j1 \neq j2$), can be written as function of the factor loadings and variances, and a residual covariance:

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

For the second approach, we can similarly calculate model-implied covariance estimates for each $\tau - th$ six-month period, using

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

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 $cov_\tau(\epsilon_{j1}, \epsilon_{j2})$ 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}), 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), than when it is due to an increase in factor volatilities (Σ_F). 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 through time, shows no long-term trend (see Schwert 1987), 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 six month period.

3.2. CAPM Models

The first asset pricing model we consider is the world CAPM (WCAPM hereafter), which contains one factor, $WMKT$, calculated as the demeaned value-weighted sum of returns on all country-industry (or country-style) portfolios. Under the WCAPM, we have:

$$R_{j,t} = E(R_{j,t}) + \beta^{WMKT}_{j,t}WMKT_t + \epsilon_{j,t}, \tag{5}$$

where β_j^{WMKT} is firm j's loading on the world market portfolio. This model only holds if the world capital market is perfectly integrated.

The second model still uses market portfolio returns as the only relevant factors, but the model also allows for exposure to a regional or local market factor, $LMKT$:

$$R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WMKT} WMKT_t + \beta_{j,t}^{LMKT} LMKT_t + \epsilon_{j,t}. \tag{6}$$

The local factor $LMKT$ is calculated in two stages. First, we compute the demeaned value-weighted sum of returns on all country-industry (or country-style) portfolios within the region. Then, this return is orthogonalized 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 six 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 the WLCAPM.

3.3. Fama-French Models

Stock return comovements may also be related to the style of the stocks involved, that is whether they are 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[6]. We use 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, a market factor ($WMKT$), a size factor ($WSMB$) and a value factor ($WHML$)[7]:

$$R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WMKT} WMKT_t + \beta_{j,t}^{WSMB} WSMB_t + \beta_{j,t}^{WHML} WHML_t + \epsilon_{j,t}. \tag{7}$$

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. Factor $WSMB$ is the demeaned value weighted sum of individual country $SMB(k)$s. 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.

[6] Campbell, Polk and Vuolteenaho (2005) find that for US stocks, the systematic risks of stocks with similar accounting characteristics are primarily driven by the systematic risks of their fundamentals.

[7] The model in Fama and French (1998) only has the market factor and the value factor. Here we incorporate a size factor, as in Fama and French (1996).

The fourth model, the world-local Fama-French model (WLFF), incorporates regional factors in addition to global factors, with returns determined by

$$\begin{aligned} R_{j,t} &= E(R_{j,t}) + \beta_{j,t}^{WMKT} WMKT_t + \beta_{j,t}^{WSMB} WSMB_t + \beta_{j,t}^{WHML} WHML_t \\ &\quad + \beta_{j,t}^{LMKT} LMKT_t + \beta_{j,t}^{LSMB} LSMB_t + \beta_{j,t}^{LHML} LHML_t + \epsilon_{j,t}. \end{aligned} \tag{8}$$

The local factors $(LMKT, LSMB, LHML)$ are all orthogonalized relative to the global factors $(WMKT, WSMB, WHML)$. Among the local factors or global factors, we do not conduct further orthogonalization, so it is possible that for instance, $LMKT$ has a nonzero correlation with $LSMB$.

3.4. 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 Connor and Korajczyk (1986) to incorporate time-series heteroskedasticity in the residuals[8]. We denote the global version of the model by WAPT, with returns determined by

$$R_{j,t} = E(R_{j,t}) + \beta_{j,t}^{WPC1} WPC1_t + \beta_{j,t}^{WPC2} WPC2_t + \beta_{j,t}^{WPC3} WPC3_t + \epsilon_{j,t}. \tag{9}$$

where $WPC1, WPC2, WPC3$ are the first three principal components from the factor analysis. 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 time-varying 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 (50-60%) of the time-series variation of returns.

[8] The asymptotic principal components procedure described in Conner and Korajczyk (1986) allows 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 procecure by allowing the covariance matrix of the factor model residuals to be time-varying. This generalization complicates the estimation of the principal components. Jones (2001) solves the estimation problem by using Joreskog's (1967) iterative algorithm.

The partial integration version of the WAPT is called the WLAPT:

$$
\begin{aligned}
R_{j,t} &= E(R_{j,t}) + \beta_{j,t}^{WPC1} WPC1_t + \beta_{j,t}^{WPC2} WPC2_t + \beta_{j,t}^{WPC3} WPC3_t \\
&\quad + \beta_{j,t}^{LPC1} LPC1_t + \beta_{j,t}^{LPC2} LPC2_t + \beta_{j,t}^{LPC3} LPC3_t + \epsilon_{j,t},
\end{aligned} \tag{10}
$$

where $LPC1, LPC2, LPC3$ are the first three principal components for the relevant region. 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 six-month period.

3.5. Heston and Rouwenhorst Model

Heston and Rouwenhorst (1994) propose a dummy variable model, which is widely used in the country-industry literature. The model postulates 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

$$
R_{j,t} = \alpha_t + D'_{C,j} * C_t + D'_{I,j} * I_t + \epsilon_{i,t}. \tag{11}
$$

The variable $D_{C,j}$ is a $n_{cou} \times 1$ country dummy vector, with the c-th element equal to one and n_{cou} is the number of countries, the variable C_t is a $n_{cou} \times 1$ country effect vector, the variable $D_{I,j}$ is a $n_{ind} \times 1$ industry dummy vector, with the i-th element equal to one and n_{ind} is the number of industries, and the variable I_t is a $n_{ind} \times 1$ industry effect vector. To estimate this model, one must impose additional restrictions: $\sum_{l=1}^{n_{cou}} w_{C,l} C_l = 0, \sum_{l=1}^{n_{ind}} w_{I,l} I_l = 0$, where $w_{C,l}$ is the market-capitalization-based country weight for the l-th 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 for each week to extract C_t and I_t. The covariance between assets $j1$ and $j2$ for a six month period consequently only depends on their respective country and industry memberships:

$$
cov(R_{j1}, R_{j2}) = cov(WMKT + C_{j1} + I_{j1}, WMKT + C_{j2} + I_{j2}) + cov(\epsilon_{j1}, \epsilon_{j2}). \tag{12}
$$

We denote this model by DCI (dummy for country and industry). It is also interesting to examine a restricted version of the DCI model. For instance, if we restrict all industry effects, I_t, to be zero, then we have a country-effects-only model, and we denote it the DC model. Similarly, if we restrict all country effects, C_t, to be zero, then we have an industry-effects-only model, and we denote it the DI model. We can derive analogous models for country-style portfolios, and we call them analogously the DCS, the DC and the DS models, with S denoting style.

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 is designed to determine whether country or industry effects dominate the variance of international portfolios and diversification benefits. The advantage of the model is that it intuitively separates returns into country and industry effects, and the relative importance of country and industry factors can vary through 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. Because of this, the model seems 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.

4. Model Estimation and Selection

In this section, we provide estimation results for our various models and determine which model provides the best fit for the sample covariance structure.

4.1. Factor Model Estimation

Table 2 presents estimation results for the country-industry and country-style portfolios. We first examine the explanatory power of the various models for returns using the adjusted R^2. On average, for country-industry portfolios, the WCAPM explains 23% of the total variance, and when region-specific market factors are added, the R^2 goes up to 36%. The WFF model explains 27% of the total variance, and together with region-specific Fama-French factors, the R^2 increases to 43%. The WAPT model explains 41% by itself, and with the addition of region-specific factors, the R^2 increases to 54%. The numbers are similar for country-style portfolios. Since the global factors and region-specific factors are orthogonal, the differences in R^2's between models with both global and local factors and models with only global factors approximately indicates how much local factors explain. The numbers are not exact because we use adjusted R^2s rather than raw R^2's. For instance, the difference in R^2 for the WLFF and WFF models goes from 23% for 1981-1985 to 11% for 2001-2005. The fact that local factors explain less of the total return variance over time suggests that the world capital market has become more integrated over time.

Even though the DCI/DSI models are estimated with weekly cross-sectional regressions, we use the model to compute a time-series R^2, comparable to the R^2's computed for the various risk-based models. The average adjusted R^2 for the DCI model is about 44% for country-industry portfolios, and 46% for country-style portfolios.

To help interpret the APT factors, Panel B explores the relation between the APT and the FF factors. If we regress the first three global APT factors on the global Fama and French factors every six-months, the time-series averages of the adjusted R^2's are respectively 73%, 28% and 19%. This indicates that the global APT factors are related to the global Fama-French factors. The regional APT factors are less related to the regional Fama-French factors, with the time-series averages of the adjusted R^2's when regressing regional APT factors on regional Fama-French factors are in the 15-30% range. We also examine the relation in the opposite direction, where we use the APT factors to explain the Fama-French factors. The APT factors have stronger explanatory power for the Fama-French factors. For the global Fama-French factors, the adjusted R^2's are 84%, 24% and 30%. For the regional Fama-French factors, the R^2's range between 10% and 50%. The significant relation between APT factors and Fama-French factors might explain why we usually obtain similar empirical results using the two models.

4.2. Model Selection Outline

Subsections 4.3 through 4.6 investigate how well our models fit the covariance structure of the base portfolio returns. To this end, we first estimate the sample covariance matrix for every half year in the sample, which we denote by $COV_{sample,\tau}, \tau = 1, ..., 52$. Given our factor model set up, 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. Based on our general factor model in equation (1), we can decompose the sample covariance as

$$COV_{sample,\tau} = COV_{\text{model},\tau} + COV_{\epsilon,\tau}, \tag{13}$$

where each element in $COV_{\text{model},\tau}$ follows from equation (3) or equation (4). The factor models only have testable implications for covariances, so we make the diagonal elements in $COV_{\text{model},\tau}$ contain 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. 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, Chamberlain and Rothschild 1983). We can define $CORR_{sample,\tau}$, $CORR_{\text{model},\tau}$ and $CORR_{\epsilon,\tau}$ analogously, by dividing each element of all the components in the covariance matrix by $[var_\tau(R_i)var_\tau(R_j)]^{0.5}$.

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,

$$\begin{aligned} MSE_{CORR} &= \frac{1}{52}\sum_{\tau=1}^{52}\{\frac{1}{\overline{W_\tau}}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,\tau}w_{j2,\tau}[CORR_{sample,\tau}(R_{j1,t},R_{j2,t}) \\ &\quad -CORR_{\text{model},\tau}(R_{j1,t},R_{j2,t})]^2\}. \end{aligned} \tag{14}$$

where t indexes different weeks, and τ indexes different six-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 where 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 Wolff 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 4.3 seeks to determine the best fitting model, whereas section 4.4 gives an idea of how various features of our factor models affect their ability to match the sample covariance matrix. Sections 4.5 and 4.6 examine the out-of-sample performance of the best models; section 4.5 focuses on forecasting covariance matrices through time, whereas section 4.6 focuses on a different set of securities, namely firm returns.

4.3. Minimizing RMSE

In this section, we conduct statistical tests to choose the best model for matching the sample correlation matrix over time. Table 3 reports the model comparison results using MSE_{CORR}. Every cell of the matrix presents the t-stat testing the significance of $diff(i,j) = MSE(\text{model } i) - MSE(\text{model } j) = \frac{1}{52}\sum_{\tau=1}^{52}[MSE_\tau(\text{model } i) - MSE_\tau(\text{model } j)] = \frac{1}{52}\sum_{\tau=1}^{52} diff_\tau(i,j)$. 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 1000 samples 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)[9].

Panel A presents results for country-industry portfolios. For example, between WLCAPM (model i) and WCAPM (model j) (third row, second column), the t-stat 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 perfect 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 improve upon the market model. The WLAPT model is significantly better than the WLCAPM ($t = -7.74$). Interestingly, point estimate indicates that the WLFF model beats the WLAPT, but 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 better, but not significantly so, than the WFF. We also examine the relative importance of country versus industry dummies by comparing the DC and DI models. For country-industry portfolios, the DCI model (with both country and industry effects) is significantly better than both the DI and the DC models. The DC model has a lower MSE than the DI model, but the difference is insignificant. We find that country dummies are slightly more important in fitting the covariance structure of country-industry portfolios than are industry dummies.

For country-style portfolios in Panel B, the results are qualitatively and quantitatively similar to the results for country-industry portfolios, except that the DC model is now significantly better than the DS model ($t = -4.56$). This is reasonable, given that we have 23 countries, but only nine

[9] 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.

different styles.

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 two out of three dummy models. Thus, we do not further report on the conditional beta model. Ghysels (1998) has already shown that the constant beta model may perform better (produce lower pricing errors) than conditional beta models because of mis-specification in the betas. However, we show in the next section that the time-varying beta approach outperforms constant beta models.

One caution about the results in Table 3 is in order. Since we estimate the covariance matrix $(n_{country} \times n_{industry}) \times (n_{country} \times n_{industry})$ using six months of weekly data (26 or 27 observations), we encounter a degrees of freedom problem[10]. To mitigate this problem, we choose subsets of the country-industry (or country-style) space to examine whether we obtain the same inference. We summarize the results in Table 4. The table reports the relative rank among the models tested for each of these subgroups. An asterisk indicates that the best model is significantly better than the other model (either WLFF or WLAPT). The first and second subsets examine country-industry portfolios, within the G5 countries, using either the most volatile and least volatile industries or the largest and smallest industries in terms of market capitalization. This gives us at most 20 portfolios per six-month period. The WLFF and WLAPT models remain best with the WLFF model becoming significantly better than any other model in the second case. This pattern persists for the third case, where our country-industry portfolios are the TMT industries in the G5 countries. Brooks and Del Negro (2004) show that the TMT industries are important in explaining the increase in world market volatility at the end of 1990s.

We also conduct the subset experiment for the country-style portfolios. Our fourth case looks at the G5 countries, and four extreme portfolios (small growth, small value, big growth and big value). WLAPT has a significantly smaller $RMSE$ than all the other models. Finally, we use the Far East countries (Australia, Hong Kong, New Zealand, and Singapore), and four extreme portfolios (small growth, small value, big growth and big value). This sample contains mostly smaller countries that

[10] Since we have 23 countries and 26 industries, the covariance matrix dimension is (23*26)*(23*26)=598*598. This means that we have 598*599/2=179101 different elements for each covariance matrix. Meanwhile, the data points we have are (26 weeks)*(23 countries)*(26 industries)=15548, which is far less than the number of statistics we estimate.

are possibly less well integrated with the world capital market. There are two interesting findings. First, the WLAPT remains the best model, and the difference between WLAPT and WLFF remains significant. This indicates that the WLAPT better captures relevant (global/regional) market-wide forces than the WLFF for less integrated markets. The second interesting finding is that the DCI model beats, although in a non-significant way, the other models except for the APT-type models. When markets are possibly segmented, the dummy variable approach manages to capture country-specific or style-specific factors relatively well.

Since the WLAPT model 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.

4.4. 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[11]. Table 5 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 5, we start with a unit-beta world CAPM model as a benchmark. That is, we take equation (5), and we assume $\beta_{WMKT} = 1$. 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 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 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 case.

The third through sixth rows explore whether other factors (such as FF factors and APT factors, or local factors) help in matching the sample correlations. For the Fama-French type models and

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

the APT models, fixing the factor loadings to their time-series or cross-sectional averages also makes it difficult for the models to match the sample correlations. If we allow the betas to vary through 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. If we include regional (local) factors, the $RMSE$ measure drops down to 0.086 for the WLFF model and to 0.088 for the WLAPT model. Hence, the Fama-French and the APT models featuring regional factors, miss the correlation on average 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 WLCAPM model. In conclusion, to match correlations, allowing free loadings on the market portfolios and the regional factors is more effective than including country and industry dummies. More generally, the Heston-Rouwenhorst model on average produces an error, which is better than any risk model with only world factors, but worse than any parsimonious risk model with regional factors.

While our results suggest that the Heston-Rouwenhorst model does not provide the best fit with stock return comovements, it has dominated the important industry-country debate. It therefore remains an important reference point. Moreover, it is interesting to view the recent country-industry debate from the correlation perspective we are taking, especially since there appears to be much disagreement about what the data tell us. 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 then argue that the phenomenon is likely temporary. 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[12]. Finally, Carrieri, Errunza and Sarkissian (2004) claim that there has been a gradual increase in the importance of industry

[12] de Roon, Eiling and Gerard (2005) and de Roon, Gerard and Hillion (2005) 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 (2005), using the Heston-Rouwenhorst model, argue that the relative importance of country factors is related to global market volatility.

factors. From Table 5, we learn that over the full sample, shutting down country dummies leads to an average correlation error of 0.309 (as for the DI model), while shutting down industry dummies leads to an average error of only 0.266 (as for the DC model). Clearly, from the perspective of their fits with international stock return comovements, country factors are more important than industry factors. We explore the time-series properties of the two models in a later section.

It is interesting to interpret the relative contributions of the various features of the risk models to the steep improvement in fit between a global CAPM with unit betas (a 0.362 error) to a Fama-French or APT model with global and local factors and time-varying betas (an error of 0.086). For example, recently a few papers have modified the Heston-Rouwenhorst approach to allow for non-unitary but time-invariant betas (see Marsh and Pfleiderer 1997, Brooks and Del Negro 2005). In the context of our risk models, the fourth and fifth columns clearly show that having a beta different from one in cross-section provides only a limited improvement. Similarly, the improvement of having the same cross-sectional betas with time variation is also limited. The last column makes it clear that we need both time-varying and cross-sectionally different betas to improve on the simpler models. 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.

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. In the context of the dummy variable model, style dummies alone produce a very bad fit to the correlations, but of course the number of style factors here is rather limited. Nevertheless, it is striking that a unit beta global CAPM model fits the correlations about as well as the style dummy model.

4.5. 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 mostly close matches the performance to the WLAPT model, and in some cases 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 Wolff (2003) to test the out-of-sample performance of various factor models. First, for each half year, we compute the candidate variance-covariance matrices, $\widehat{V}_k$, where k indexes our various models, and 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, this portfolio surely is ill-behaved when the sample covariance matrix is used as an estimate for V because of the dimensionality problem mentioned earlier. We indeed verified that the sample covariance matrix typically had a huge condition number and was practically not invertible. Second, we hold this portfolio during the next six months and compute its volatility using weekly returns. Third, we repeat these steps for each six 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. We conduct this exercise not only over the space of all country-industry or country-style portfolios, but also over the more limited asset spaces considered in Table 4.

We report the results in Table 6. First, the risk-based models perform uniformly and considerably better than the Heston-Rouwenhorst models, often producing average volatilities that are well over 1% lower. Second, no model consistently produces the lowest variance over the 7 test cases we consider. Third, the WLAPT models only feature twice among the top two models, and the WLFF never does. However, the performance of all risk-based models is quite close. There is only one case (all country-industry portfolios), for which the WLFF model performs worse by more than 1% relative to the best model, the more parsimonious WFF model. 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.

4.6. Fit for Firm Returns

Our model has been applied and tested for country-industry and country-style portfolios. Here we test whether the WLFF and WLAPT models also outperform the Heston-Rouwenhorst type models for individual firm returns. We choose four firms as examples: Novartis (a large phamaceutical firm headquartered in Switzerland), Merck (a large phamaceutical firm headquartered in the US), IBM (a large info tech firm headquartered in the US) and Nihon Unisys (a mid-size info tech firm headquartered in Japan). We select the four firms from different countries, different industries and different styles to emphasize the country and industry effects. To calculate the WLAPT and WLFF model implied correlation for every six-month period, we first estimate the factor loadings for the four firms. The implied correlations then follow from equation (3). To calculate the correlations implied by the dummy variable models for every six-month period, we first identify each firm's country, industry and style, and the model implied covariance is calculated as in equation (12). Consequently, we are applying a model that was derived for country-industry portfolios or country-style portfolios in an "out-of-sample" experiment with firm level data.

Table 7 reports some properties of the sample correlations of the firm returns and the implied correlations from the WLFF and WLAPT model and from the dummy variable models DCI and DCS. The first pair is Novartis and Merck, which are from the same industry/style but from different countries. The average correlations generated by the WLFF/WLAPT models are much closer to the sample correlations than the other models are, and the correlations are close to the sample correlations than the correlations produced by the DCI and DCS models. Hence, the WLFF/WLAPT models better match comovement dynamics between Novartis and Merck.

We also examine another five pairs, Novartis and Nihon Unisys, Novartis and IBM, Merck and Nihon Unisys, Merck and IBM, and Nihon Unisys and IBM. The advantage of the WLFF/WLAPT models over the DCI/DCS models remains, and it is even more dramatic in terms of matching the time-series dynamics of comovements. The correlation between the model and sample comovements is at least 65% for the WLFF/WLAPT models, but it can drop to as low as 20% for the dummy variable models. The dummy variable approach appears not flexible enough to capture firm level comovements, while the WLFF/WLAPT models perform well for this set of firm returns.

5. 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 5.1, with a discussion of the general methodology, which we apply to our base portfolios. In section 5.2, we consider the long-run behavior of correlations between country returns, addressing the question 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 5.3, we consider the implications of our analysis for the country-industry debate. In Section 5.4, we further investigate the role of "style" as a driver of international return correlations. In Section 5.5 we link our framework briefly to the contagion literature, and the recent debate about trends in idiosyncratic variances.

5.1. Methodology and Trends in Base Portfolio Correlations

We define the following comovement measures for average portfolio level covariances,

$$\begin{aligned}
\gamma^{COV}_{sample,\tau} &= \frac{1}{\overline{W_\tau}} \sum_{j1=1}^{n_{PORT}} \sum_{j2>j1}^{n_{PORT}} w_{j1,\tau} w_{j2,\tau} cov_\tau(R_{j1,t}, R_{j2,t}) \\
&= \frac{1}{\overline{W_\tau}} \sum_{j1=1}^{n_{PORT}} \sum_{j2>j1}^{n_{PORT}} w_{j1,\tau} w_{j2,\tau} cov_\tau(\beta'_{j1}F_t, \beta'_{j2}F_t) + \frac{1}{\overline{W_\tau}} \sum_{j1=1}^{n_{PORT}} \sum_{j2>j1}^{n_{PORT}} w_{j1,\tau} w_{j2,\tau} cov_\tau(\epsilon_{j1,t}, \epsilon_{j2,t}) \\
&= \gamma^{COV}_{risk,\tau} + \gamma^{COV}_{idio,\tau}, \qquad (15)
\end{aligned}$$

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

$$\gamma^{CORR}_{sample,\tau} = \gamma^{CORR}_{risk,\tau} + \gamma^{CORR}_{idio,\tau}. \qquad (16)$$

Figure 1 presents the time-series of γ^{CORR}_{sample}, γ^{CORR}_{risk} and γ^{CORR}_{idio} for both country-industry and country-style portfolio correlations. Panel A of Figure 1 reports the sample correlations, γ^{CORR}_{sample}. On average, country-style portfolios have slightly higher (by 0.05-0.10) correlations, especially over recent years, than country-industry portfolios. We present the γ^{CORR}_{risk} and γ^{CORR}_{idio} decomposition in Panels B and C, for the two types of portfolios. The benchmark model for the decomposition is the WLFF model. The graphs look nearly identical if we use the WLAPT model. However, using the WLFF model, we can 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 correlation. The residual correlations at the bottom of each figure are small in terms of magnitude (less than 0.10). Figure 1 shows that none of the correlations for the country-industry and country-style portfolio display any obvious trends. Reflecting the good fit of the factor models, the idiosyncratic comovements are pretty much flat at zero. We will mostly 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^{CORR}_{sample} and γ^{CORR}_{risk}. 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

$$y_\tau = \alpha_0 + \alpha_1 \tau + u_\tau, \tag{17}$$

where y_τ is the variable of interest, and τ is a linear time trend. We use the PS1 test in Vogelsang for testing $\alpha_1 = 0$. The test statistic is robust to $I(0)$ and $I(1)$ error terms.[13]

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 also below). While Vogelsang's test has good size and power properties, the latter both asymptotically and in finite samples, 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 non-parametrically estimate the error variance needed in the test. In fact, tests based on this kernel maximize power among a wide range of kernels.

Table 8 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, $\Sigma_{F\tau}$ to their sample means, denoted as TSA (time-series average) B and TSA Σ, 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 potential trend behavior. For all these comovement measures, we report seven statistics: the sample average, the sample

[13] 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.

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 1 in absolute value. Consequently, we do not find a significant time trend in correlations for the base portfolios. 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 will re-examine this long-term behavior for meaningful sub-groups of portfolios in the next few sub-sections.

The table reveals that the average country-industry correlation is 0.37, but it shows 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 over-predict 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.

5.2. 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* on 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 non-parametric. 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.[14] 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 (2006).

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), Fratscher (2002), and Baele (2005) focus on time-variation in betas directly to measure financial market integration.

Table 9 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 towards 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 those two regions and all countries from the perspective of a US investor.

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

First of all, 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 US and Europe. Hence, the general picture is that of an integrating North American and European world, with Asia left out for now.

Second, we examine the sources of the trends by either fixing the betas or covariances at their sample averages. We start with the US 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 sparser before 1986. 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 then perhaps not surprising that there is indeed a significant trend for the correlations between the U.S. and Europe, even at the two-sided 5% level, when the sample is stated 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. Yet, the magnitude of the trend coefficient is larger with fixed volatilities, so even though volatility bias may play a role, time-varying betas may still be the dominant factor. Therefore, it is interesting to consider the regional source of this trend. Panel C shows trend results for the US with different country groups in Europe, described in the table. These country groups include the European Union (EU) countries, Core EU (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 countries in addition include the UK, Denmark, Sweden, and Norway. Focusing on the 1986-2005 sample, all sub-groups 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 due to the first part of the sample, where the factor models over-estimate 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 US-Europe correlations. There is a nearly significant trend when betas are fixed 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 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.

5.3. The Industry-Country Debate

The industry-country 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 into industry portfolios leads to equally well-diversified portfolios. Hence, country and industry return correlations can be meaningfully compared.

Table 10 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.

Why did 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 1990's 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 10. 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 (2006), using a very different methodology, reach similar conclusions. 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 missed the rather dramatic rise in the cross-sectional variation of betas towards the end of the nineties.

5.4. 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, 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 11. 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 11 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 1990's. However, the differential has since reversed. In Panel C of Table 11, 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.

5.5. Contagion and Idiosyncratic Risk

This issue of increased correlation arises 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 correlations 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, Pindyk and Rotemberg 1990, and Kallberg and Pasquariello 2005). 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 $\gamma^{CORR}_{idio,\tau}$ can be viewed as a time-varying contagion measure.[15] 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,

$$\begin{aligned}\sigma^2_{sample,\tau} &= \sum_{j=1}^{n} w_{j,\tau} var_\tau(R_{j,t}) \\ &= \sum_{j=1}^{n} w_{j,\tau} var_\tau(\beta'_{j\tau}F_t) + \sum_{j=1}^{n} w_{j,\tau} var_\tau(\epsilon_{j,t}) \\ &= \sigma^2_{risk,\tau} + \sigma^2_{idio,\tau},\end{aligned} \tag{18}$$

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 do this decomposition for our country-industry and country-style portfolios, we find no evidence of a trend at all. 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, we revisit the issue with firm level data.

6. Conclusions

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

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

Using country-industry and country-style portfolios as benchmarks, 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 was 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 can re-examine the industry-country 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) leads to different conclusions.

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, Harvey, Lundblad and Siegel (2007) 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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Table 1. Summary statistics for firm returns

All numbers reported are time-series averages for the relevant statistics. The sample period is January 1980 to December 2005. For US 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 US 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 global market cap
CANADA	198001	19.72%	599	0.90	489	330	2.7%
FRANCE	198001	19.42%	993	1.05	451	580	3.6%
GERMANY	198001	12.22%	1042	0.80	460	522	4.0%
ITALY	198001	17.46%	1135	0.92	205	272	1.8%
JAPAN	198001	15.49%	1538	0.71	1506	2417	23.7%
UNITED KINDOM	198001	17.03%	890	0.88	1142	1168	9.1%
UNITED STATES	198001	16.72%	1241	0.81	4013	5228	44.9%
AUSTRALIA	198001	19.90%	571	0.87	417	215	1.5%
AUSTRIA	198001	14.28%	300	1.34	70	26	0.2%
BELGIUM	198001	16.97%	640	1.23	92	74	0.5%
DENMARK	198001	19.26%	301	1.64	137	48	0.3%
FINLAND	198701	18.21%	776	0.96	104	97	0.5%
GREECE	198801	26.06%	218	0.75	201	55	0.3%
HONG KONG	198001	21.50%	771	1.25	320	263	1.7%
IRELAND	198001	21.74%	629	1.21	42	31	0.2%
NETHERLANDS	198001	16.75%	1663	1.44	126	255	1.6%
NEW ZEALAND	198601	16.35%	395	0.91	55	18	0.1%
NORWAY	198001	21.22%	331	1.32	108	45	0.3%
PORTUGAL	198801	14.50%	512	1.18	70	38	0.2%
SINGAPORE	198001	17.56%	585	0.91	161	92	0.7%
SPAIN	198601	21.55%	1975	0.89	109	240	1.4%
SWEDEN	198001	19.55%	613	0.84	196	144	0.9%
SWITZERLAND	198001	12.96%	1376	1.17	189	306	1.9%

Table 2. Factor model estimation results

In Panel A, for the risk-based models, the adjusted R^2's are first averaged across portfolios (equally weighted), and then averaged over different time periods. For the DCI/DSI models, the factor realizations are estimated using weekly cross-sectional data. Then we use the model to compute a time-series R^2, comparable to the R^2's computed for the various risk-based models. Panel B provides statistics relating APT factors to the Fama-French factors. The left half of Panel B reports the time-series average of the adjusted R-square of regressing individual APT factors on the Fama-French factors from the relevant regions. The right half of Panel B reports the time-series average of the adjusted R-square of regressing individual Fama-French factors on different APT factors. The sample period is January 1980 to December 2005. For US 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 US dollars. Model WCAPM is the global CAPM, in which the only factor is the global market portfolio return (WMKT). Model WFF is the global Fama-French three factor model, in which the factors are the global market portfolio return (WMKT), the global SMB (WSMB) portfolio, and the global HML (WHML) portfolio. Model WAPT is the global APT model with three factors. 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).

Panel A. Adjusted R^2's

	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI/DCS
Country-industry portfolios							
whole sample	23%	36%	27%	43%	41%	54%	44%
1981-1985	30%	47%	34%	57%	53%	69%	50%
1986-1990	23%	38%	27%	45%	43%	59%	46%
1991-1995	19%	32%	20%	37%	36%	50%	40%
1996-2000	17%	25%	20%	31%	29%	41%	43%
2001-2005	27%	35%	32%	43%	42%	52%	39%
Country-style portfolios							
whole sample	21%	34%	27%	45%	44%	58%	46%
1981-1985	26%	44%	32%	56%	54%	70%	49%
1986-1990	21%	33%	25%	43%	44%	59%	47%
1991-1995	17%	31%	20%	40%	41%	55%	43%
1996-2000	16%	25%	22%	36%	33%	46%	49%
2001-2005	26%	35%	35%	49%	48%	58%	43%

Panel B. APT factors vs. Fama-French factors

	Independent Variables	Dependent variables			Independent Variables	Dependent variables		
		PC1	PC2	PC3		MKT	SMB	HML
global	WFF	73%	28%	19%	WAPT	84%	24%	30%
North America	WFF	16%	22%	20%	WAPT	41%	14%	14%
	LFF	28%	18%	14%	LAPT	32%	18%	15%
Europe	WFF	11%	11%	9%	WAPT	53%	14%	11%
	LFF	23%	15%	17%	LAPT	24%	15%	14%
Far East	WFF	10%	11%	12%	WAPT	47%	15%	13%
	LFF	25%	21%	20%	LAPT	31%	18%	17%

Table 3. Model fit: matching the sample portfolio correlation matrix

Every cell (i,j) reports the t-stat for MSE(model i)-MSE(model j). The MSE statistic is defined in equation (14). The standard errors accommodate 4 Newey-West (1987) lags. The bold fonts indicate that the t-statistic is significant at the 5% level when we use a bootstrapped empirical distribution for the t-statistic. The sample period is January 1980 to December 2005. For US 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 US dollars. 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. 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). Model DI (DS) is the restricted dummy variable model with only industry (style) dummies. Model DC is the restricted dummy variable model with only country dummies. 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 j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
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**		
DI	**5.76**	**6.44**	**7.51**	**7.46**	**5.61**	**7.39**	**5.54**	
DC	2.24	**6.15**	**3.24**	**6.78**	**4.28**	**6.79**	**5.11**	-1.36

Panel B: country-style portfolio correlation matrix

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
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**		
DS	**5.34**	**6.75**	**6.37**	**7.18**	**6.26**	**7.07**	**5.99**	
DC	-1.10	**4.48**	0.10	**5.34**	1.62	**5.36**	**3.99**	**-4.56**

Panel C: conditional factor models

t-stat	Model j								
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DC	DI
Conditional beta	2.44	**6.21**	**4.25**	**7.13**	**5.00**	**6.93**	**4.79**	**-6.43**	2.59

Table 4. Model fit for subsets of portfolios

We report the rank over all models for the WLFF and WLAPT models, with 1 meaning the lowest possible RMSE or the best model, etc. An asterisk next to 1 means that the best model is significantly better than the other models. We consider five cases, described in the first column. The sample period is January 1980 to December 2005. For US 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 US dollars. There are a total of 8 models. 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. 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).

	Rank of WLFF	Rank of WLAPT
Case I: G5 countries, least volatile industries (food and utility) and most volatile industries (info tech and electronics)	2	1
Case II: G5 countries, smallest industries (household and recreation) and biggest industries (finance and oil and gas)	1*	2
Case III: G5 countries, TMT industries (Telecom, Media and Info Tech)	1*	2
Case IV: G5 countries, small growth, small value, big growth and big value portfolios	2	1*
Case V: Far East countries (Australia, Hong Kong, New Zealand, Singapore), small growth, small value, big growth and big value portfolios	4	1*

Table 5. 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 (13). Unit beta means the global market beta is set to be one. Cross-sectional average beta means that all the betas in each model are set to the cross-sectional average of betas within each six-month period. Time-series average 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. The sample period is January 1980 to December 2005. For US 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 US dollars. 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. 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). Model DI (DS) is the restricted dummy variable model with only industry (style) dummies. Model DC is the restricted dummy variable model with only country dummies.

Panel A: Country-industry portfolios

	Unit beta	Cross-section average betas		Time-series average betas		Free beta	
	RMSE	RMSE	% of unit beta RMSE	RMSE	% of unit beta RMSE	RMSE	% of unit beta RMSE
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%
DI						0.309	85%
DC						0.266	73%

Panel B: country-style portfolios

	Unit beta	Cross-section average betas		Time-series average betas		Free beta	
	RMSE	RMSE	% of unit beta RMSE	RMSE	% of unit beta RMSE	RMSE	% of unit beta RMSE
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%
DS						0.363	96%
DC						0.188	50%

Table 6. 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 six months and compute its volatility using weekly returns. We repeat these steps for each six month period and average the computed volatilities over the full sample. In addition to all portfolios, we consider five cases of portfolios subgroups (see Table 4 for full descriptions). The sample period is January 1980 to December 2005. For US 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 US dollars. 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. 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). Model DI (DS) is the restricted dummy variable model with only industry (style) dummies. Model DC is the restricted dummy variable model with only country dummies.

Panel A. country industry portfolios

	Case I: all portfolios	Case II: G5 volatility portfolios	Case III: G5 size portfolios	Case IV: G5 TMT portfolios
WCAPM	0.0994	**0.0954**	0.1130	0.1263
WLCAPM	0.0964	0.0961	0.1139	0.1233
WFF	0.0980	0.0965	**0.1125**	0.1252
WLFF	**0.0961**	0.0981	0.1153	0.1235
WAPT	0.0970	0.0998	0.1132	0.1246
WLAPT	0.0974	0.0991	0.1150	**0.1232**
DCI	0.1130	0.1246	0.1227	0.1345
DC	0.1113	0.1313	0.1177	0.1320
DI	0.1249	0.1284	0.1295	0.1326

Panel B. country style portfolios

	Case I: all portfolios	Case II: G5 portfolios	Case III: Far East portfolios
WCAPM	0.0970	0.1079	0.1486
WLCAPM	**0.0933**	0.1034	0.1476
WFF	0.0956	0.1071	0.1476
WLFF	0.0946	0.1048	0.1475
WAPT	0.0934	0.1050	**0.1461**
WLAPT	0.0949	**0.1028**	0.1477
DCI	0.1128	0.1186	0.1565
DC	0.1035	0.1177	0.1517
DI	0.1141	0.1192	0.1564

Table 7. Firm level comovements

We report the average sample correlations between a number of firms and copare it to the correlation implied by different models. We also report the time-series correlation between the correlation in the data and the one implied by the models. The sample period is January 1980 to December 2005. All the returns are denominated in US dollars. Model WLFF is a Fama-French type model with factors from both the global and regional markets. Model WLAPT is an APT model with three factors from both the global and regional markets. Model DCI/DCS is the dummy variable model from Heston and Rouwenhorst (1994).

	correlation	Correl (sample correl ,model correl)
Novartis and Merck		
data	25%	
WLFF	31%	70%
WLAPT	31%	66%
DCI	54%	65%
DCS	45%	51%
Novartis and Nihon Unisys		
data	7%	
WLFF	10%	69%
WLAPT	9%	85%
DCI	15%	62%
DCS	28%	48%
Novartis and IBM		
data	12%	
WLFF	24%	70%
WLAPT	22%	82%
DCI	21%	42%
DCS	44%	32%
Merck and Nihon Unisys		
data	5%	
WLFF	9%	73%
WLAPT	12%	76%
DCI	22%	25%
DCS	23%	36%
Merck and IBM		
data	22%	
WLFF	53%	76%
WLAPT	49%	86%
DCI	66%	58%
DCS	98%	20%
Nihon Unisys and IBM		
data	7%	
WLFF	13%	80%
WLAPT	14%	65%
DCI	51%	44%
DCS	21%	50%

Table 8. 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 (16). 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 time-series average (TSA), and the third version allows free factor covariances but fixes betas to be at their time-series average. 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 is 2.152. The sample period is January 1980 to December 2005.

Panel A. Country-industry portfolio correlations

	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA
Factor cov		Free	TSA	Free
mean	0.366	0.370	0.514	0.447
std. dev.	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

	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA
Factor cov		Free	TSA	Free
mean	0.447	0.449	0.644	0.515
std. dev.	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

Table 9. 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 US 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 (16). 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 time-series average (TSA), and the third version allows free factor covariances but fixes betas to be at their time-series average. 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). In Panels A and E, t-dan test statistics are reported at 5% level; in Panels B, C and D, we present t-dan test statistics at both 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 is 2.152. The 10% critical value (two sided) for t-dan is 1.710, and for t-ps is 1.720. The sample period is January 1980 to December 2005.

Panel A. Correlations

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

Panel B. US vs Europe

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

Panel C. US and different areas within Europe (only data correlations γ_{sample}^{CORR})

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

Panel D. European countries

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

Panel E. Cross-Correlation within Europe (1986-2005), γ_{sample}^{CORR} only

European Areas	γ_{sample}^{CORR} CEU NCEU	γ_{sample}^{CORR} EURO NEURO	γ_{sample}^{CORR} CEU	γ_{sample}^{CORR} NCEU	γ_{sample}^{CORR} EURO	γ_{sample}^{CORR} NEURO	γ_{sample}^{CORR} EU
mean	0.574	0.567	0.668	0.530	0.626	0.553	0.575
std. dev.	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**

Table 10. 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 (16). 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 time-series average (TSA), and the third version allows free factor covariances but fixes betas to be at their time-series average. 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 is 2.152. The 10% critical value (two sided) for t-dan is 1.710, and for t-ps is 1.720. The sample period is January 1980 to December 2005.

Panel A. Industry portfolio correlations

	With TMT industries				Without TMT industries			
	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA		Free	Free	TSA
Factor cov		Free	TSA	Free		Free	TSA	Free
mean	0.630	0.639	0.957	0.716	0.638	0.645	0.978	0.723
std. dev.	0.116	0.114	0.474	0.083	0.118	0.118	0.477	0.084
correl(.,data)	100%	100%	-3%	88%	100%	100%	-3%	88%
b-dan	0.0000	0.0000	0.0016	0.0009	-0.0001	-0.0003	0.0017	0.0010
t-dan	-0.019	0.012	0.005	0.787	-0.076	-0.147	0.006	0.774
b-ps	-0.0005	-0.0005	0.0013	0.0008	-0.0005	-0.0007	0.0019	0.0009
t-ps	-0.246	-0.220	0.012	0.483	-0.211	-0.278	0.018	0.508

Panel B. Country portfolio correlation γ – industry portfolio correlation γ for full sample

	With TMT industries				Without TMT industries			
	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA		Free	Free	TSA
Factor cov		Free	TSA	Free		Free	TSA	Free
mean	-0.245	-0.250	-0.400	-0.245	-0.253	-0.256	-0.422	-0.252
std. dev.	0.142	0.141	0.295	0.119	0.148	0.151	0.307	0.121
correl(.,data)	100%	100%	75%	88%	100%	100%	75%	88%
b-dan	0.0051	0.0051	0.0044	0.0040	0.0052	0.0054	0.0043	0.0040
t-dan	0.090	0.110	0.035	0.109	0.083	0.091	0.041	0.082
b-ps	0.0039	0.0039	0.0017	0.0029	0.0039	0.0041	0.0011	0.0028
t-ps	0.121	0.136	0.026	0.120	0.110	0.120	0.019	0.098

Panel C. Country portfolio correlation γ – industry portfolio correlation γ for 1991 - 2000

	With TMT industries				Without TMT industries			
	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta		Free	Free	TSA		Free	Free	TSA
Factor cov		Free	TSA	Free		Free	TSA	Free
mean	-0.289	-0.294	-0.564	-0.281	-0.300	-0.302	-0.598	-0.288
std. dev.	0.230	0.228	0.587	0.197	0.249	0.254	0.609	0.209
correl(.,data)	100%	100%	80%	91%	100%	100%	80%	91%
b-dan	0.0220	0.0217	0.0456	0.0178	0.0240	0.0243	0.0473	0.0189
t-dan	2.136	2.217	0.061	0.456	1.739	1.658	0.061	0.325
b-ps	0.0197	0.0194	0.0399	0.0162	0.0213	0.0214	0.0423	0.0168
t-ps	2.290	2.378	0.154	0.975	1.915	1.878	0.158	0.749

Table 11. 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 (16). 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 time-series average (TSA), and the third version allows free factor covariances but fixes betas to be at their time-series average. 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 is 2.152. The 10% critical value (two sided) for t-dan is 1.710, and for t-ps is 1.720. The sample period is January 1980 to December 2005.

Panel A. style small versus style big

	small	big	small-big			
	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	0.357	0.457	-0.100	-0.095	-0.006	-0.078
std. dev.	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

Panel B. style growth versus style value

	growth	value	growth-value			
	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	0.364	0.359	0.005	0.003	0.033	0.021
std. dev.	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

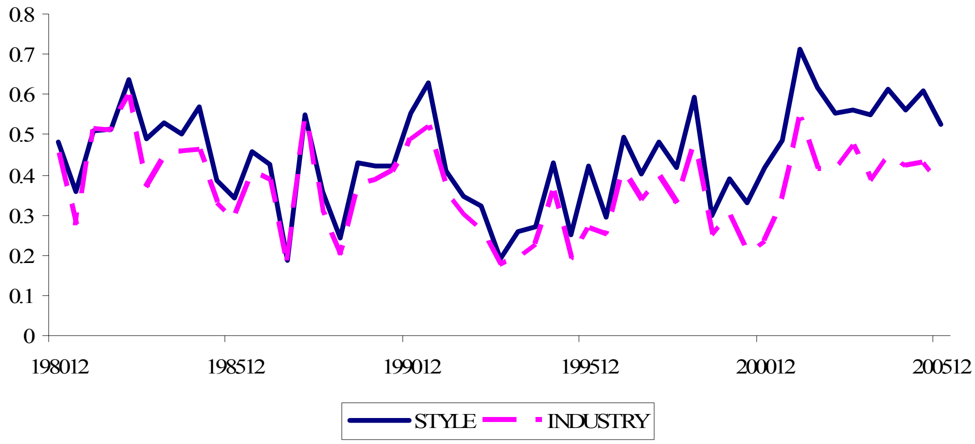
Panel C. style big growth portfolio γ – style small value portfolio γ

	big growth	small value	big growth – small value			
	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{sample}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}	γ_{risk}^{CORR}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	0.345	0.235	0.111	0.109	0.098	0.108
std. dev.	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

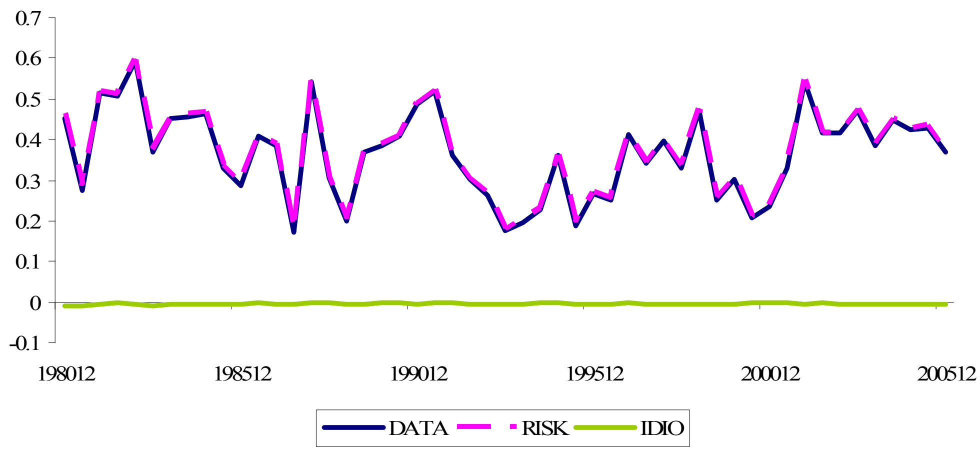
Figure 1. Time-series of portfolio level correlation measure

The data correlation and its decomposition are defined in equation (16), 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 to December 2005.

Panel A. Data correlations for country-industry portfolios and country-style portfolios



Panel B. Decomposition for country industry portfolios

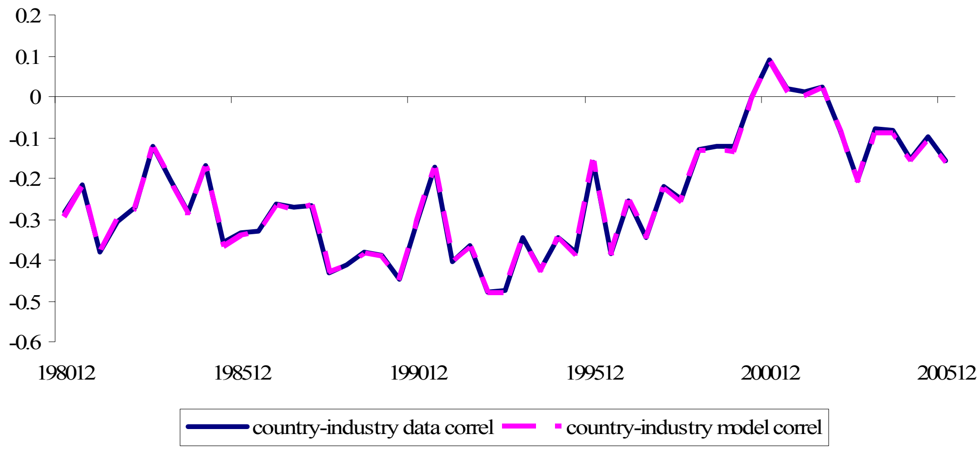


Panel C. Decomposition for country style portfolios

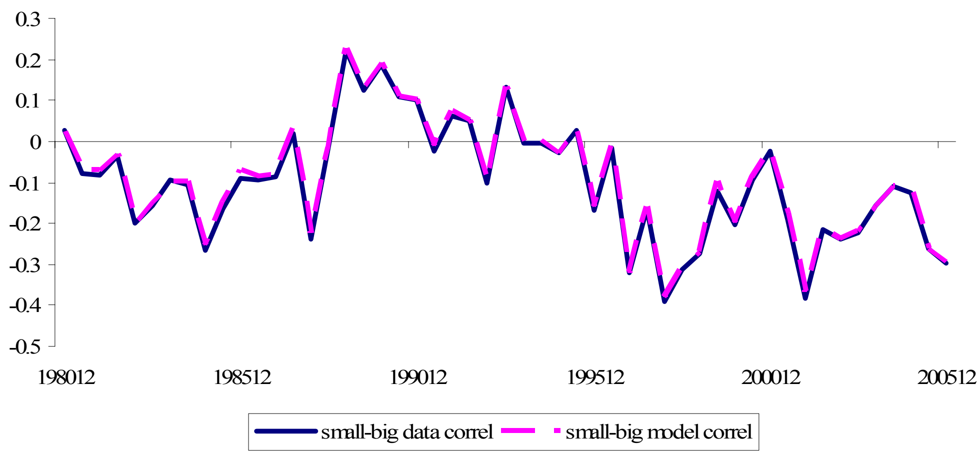
Figure 2. Time-series of portfolio correlation differences

The figure graphs the difference between two γ_{sample}^{CORR}'s (or γ_{risk}^{CORR}'s) computed using different portfolios. See equation (16) for the definition of γ_{sample}^{CORR} and γ_{risk}^{CORR}. The sample period is January 1980 to December 2005.

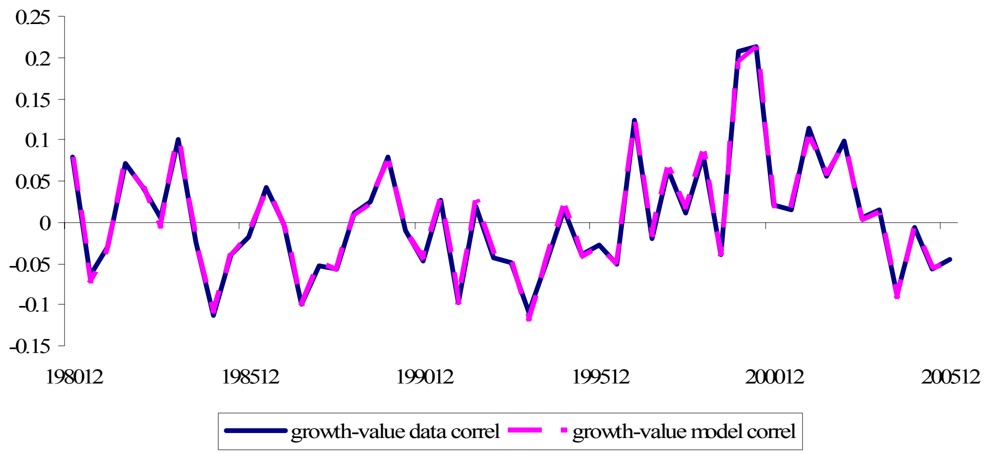
Panel A. Country portfolios minus industry portfolios



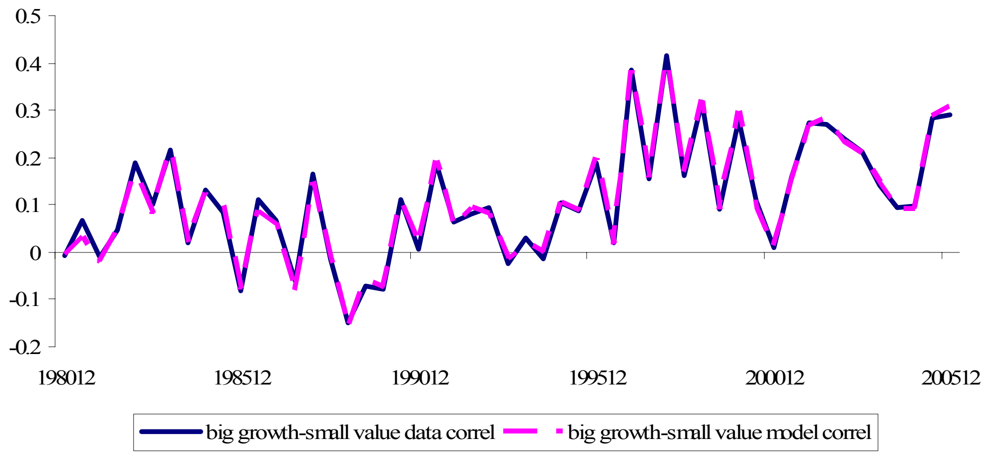
Panel B. Style small portfolios minus style big portfolios



Panel C. Style growth portfolios minus style value portfolios



Panel D. Style large growth portfolios minus style small value portfolios



Appendix. Match SIC industry classification with FTSE industry classification

DataStream provides FTSE level 4 industries, and French's website provides SIC 30 industries.

merged	FTSE level 4 industries		SIC 30 industries		
1	1	mining	17	Mines	Precious Metals, Non-Metallic, and Industrial Metal
2	2	oil and gas	19	Oil	Petroleum and Natural Gas
			18	Coal	Coal
3	3	chemicals	9	Chems	Chemicals
4	4	construction	11	Cnstr	Construction and Construction Materials
5	5	forestry and paper	24	Paper	Business Supplies and Shipping Containers
6	6	steel and other metals	12	Steel	Steel Works Etc
7	9	electronics and electrical equipments	14	ElcEq	Electrical Equipment
8	10	engineering and machinery	13	FabPr	Fabricated Products and Machinery
9	11	automobiles	15	Autos	Automobiles and Trucks
10	12	household goods and textiles	6	Hshld	Consumer Goods
			7	Clths	Apparel
11	13	beverages	2	Beer	Beer & Liquor
	14	food producers and processors	1	Food	Food Products
	27	food and drug			
12	15	health	8	Hlth	Healthcare, Medical Equipment, Pharmaceutical Products
	17	personal care			
	18	pharmaceuticals			
13	19	tobacco	3	Smoke	Tobacco Products
14	20	distributors	26	Whlsl	Wholesale
15	21	retailers	27	Rtail	Retail
16	22	leisure, entertainment and hotesl	4	Games	Recreation
	24	restaurants, pubs and breweries	28	Meals	Restaraunts, Hotels, Motels
17	23	media and photography	5	Books	Printing and Publishing
18	26	transport	25	Trans	Transportation
19	28	telecom services	21	Telcm	Communication
20	29	electricity	20	Util	Utilities
	30	gas distribution			
	31	water			
21	34	banks	29	Fin	Banking, Insurance, Real Estate, Trading
	35	insurance			
	36	life assurance			
	37	investment companies			
	38	real estate			
	39	specialty and other finance			
22	7	aerospace and defence	16	Carry	Aircraft, ships, and railroad equipment
23	8	diversified industrials	10	Txtls	Textiles
24	16	packaging	22	Servs	Personal and Business Services
	25	support services			
	33	software and computer services			
25	32	information technology hardware	23	BusEq	Business Equipment
26	40	ineligible	30	Other	Everything Else