NBER WORKING PAPER SERIES

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Working Paper 11906
http://www.nber.org/papers/w11906

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2005

We are very grateful to Tim Vogelsang who provided code for the linear time trend test. Correspondence Address: Geert Bekaert, Columbia Business School, Uris Hall 802, 3022 Broadway, New York, NY 10027. Tel.: 212-854-9156. E-mail: gb241@columbia.edu.

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NBER Working Paper No. 11906
December 2005
JEL No. C52, G11, G12

ABSTRACT

We examine international stock return comovements using country-industry and country-style 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, excpet for the European stock markets. Second, the increasing imporatnce of industry factors relative to country factors was a short-lived, temporary phenomenon. Third, we find no evidence for a trend in idiosyncratic risk in any of the countries we examine.

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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 and Martin (1998). 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. Finally, in an influential article, Campbell, Lettau, Malkiel and Xu (2001) argue that the idiosyncratic risk of individual firms has markedly increased in the US. This is an important fact for the study of comovements, because everything else equal, it would lower correlations between firm returns.

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 –2003. 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. Given such a background, we want to allow for maximum flexibility in the modeling of return comovements. We view stock return comovements from the perspective of a linear factor model with time-varying factor exposures (betas), time-varying factor volatilities, and potentially time-varying idiosyncratic volatilities. 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. Surprisingly, much of the literature on 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.

We examine how well the various factor models fit the stock return comovements of our portfolios. We find that risk-based models fit stock return comovements much better than the Heston-Rouwenhorst model. We then select the best model to answer several salient questions.

First, we examine whether there are time trends in stock return comovements, focusing primary on country return correlations. We also characterize the behavior of country return correlations over time, decomposing them into betas, factor covariances and idiosyncratic covariances. We only find a significant upward trend for stock return correlations within Europe. Second, 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. Third, 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. Finally, we detect no evidence at all of a trend in firm-level idiosyncratic variances over our sample period, including the US.

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, whereas section 6 focuses on firm level returns. Section 7 concludes.

2. Data

We study weekly portfolio returns from 23 developed markets. We choose to study returns at a weekly frequency as a balance between data availability and non-synchronous trading around the world. 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]. The selection of developed countries is obtained from 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 2003:12, for 1253 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 $181 million for Austria and $1543 million for Japan. The average BM is 0.69 for Japan and 1.46 for Belgium. 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. Because we use CRSP data for US firms, the U.S. industry identification is from SIC. Since we want to look at industries at a relatively aggregate level that also preserves cross-sectional differences, we use the FTSE level 4 classification, which has 40 industries, and we match these to the SIC 30 industries classification. The main issue with SIC coding is that it does not have a separate technology industry, whereas the issue with respect to FTSE coding is that it has relatively too many industries, some of which are closely related. We therefore group the SIC and FTSE classifications to have a smaller number of industries that approaches the number of countries in our sample, resulting in 26 industries. Table 2 shows the reconciliation between the SIC system and the FTSE system. To form country-industry portfolios,

[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.

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 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 on firms in the portfolio. All portfolios are required to have at least 5 firms.

A preliminary investigation of the raw data reveals that quite a few country portfolios have higher volatilities over the last five years in our sample, 1998-2003. Later in this article, we will formally investigate whether these higher levels represent a trend. In addition, the TMT industries (info tech, media, and telecom) witnessed a tremendous increase in volatility during 1998-2003, which is consistent with findings of Brooks and Del Negro (2003). This increase in volatility is also noticeable for the style portfolios, especially for the small firms.

3. Models and Empirical Design

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

3.1. General Model

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

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

[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.

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 global shocks (zero-mean factors), $\beta_{j,t}^{reg}$ 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. Many articles (see for instance, Bekaert and Harvey 1995 and Baele 2005) have noted that the process towards market integration may not be smooth. Maximum flexibility in the model with regard to the importance of global versus country-specific factors is necessary. The above general model allows exposure to global factors and regional factors, consistent with full market integration, partial world market integration or regional integration.

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. We choose to use regional factors rather than country factors as local factors because Brooks and Del Negro (2003) 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. Empirically, we re-estimate all the models every six months, allowing idiosyncratic volatilities, factor volatilities and the betas to vary over time.

While the implications of a linear factor model for covariances and correlations are well known, it is instructive to review how they relate to the current debate on the time-variation in cross-country correlations and the industry-country debate. Let $F_t = \{(F_t^{glo})', (F_t^{reg})'\}'$ be the $(k^{glo} + k^{reg}) \times 1$ factor vector for time t, let $\Sigma_F = cov(F_t, F_t)$ be a $(k^{glo} + k^{reg}) \times (k^{glo} + k^{reg})$ factor covariance matrix, and let $B_j = \{(\beta_j^{glo})', (\beta_j^{reg})'\}'$ be a $(k^{glo} + k^{reg}) \times 1$ loading vector. The covariance of two returns, R_{j1}, R_{j2} $(j1 \neq j2)$, can be written as function of the factor loadings, and a residual covariance:

$$cov(R_{j1}, R_{j2}) = B_{j1}' \Sigma_F B_{j2} + cov(\epsilon_{j1}, \epsilon_{j2}). \tag{2}$$

If the factor model fully describes stock return comovements, the residual covariance $cov(\epsilon_{j1}, \epsilon_{j2})$ 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).

Let us assume these covariances to be zero for now. From equation (2), covariances between two assets estimated in different periods can increase through the following two channels: an increase in the factor loadings B 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 are decreasing in idiosyncratic volatility. 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. We now consider several special cases of the general factor model.

3.2. CAPM Models

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

$$R_{j,t} = E(R_{j,t}) + \beta_j^{WMKT} WMKT_t + \epsilon_{j,t}, \tag{3}$$

where β_j^{WMKT} is firm j's loading on the world market portfolio[5]. 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, $LMKT$:

$$R_{j,t} = E(R_{j,t}) + \beta_j^{WMKT} WMKT_t + \beta_j^{LMKT} LMKT_t + \epsilon_{j,t}. \tag{4}$$

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

[5] We drop the subscript t of β for simplicity. We estimate β every six-month period, during which it is assumed constant.

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]:

$$R_{j,t} = E(R_{j,t}) + \beta_j^{WMKT} WMKT_t + \beta_j^{WSMB} WSMB_t + \beta_j^{WHML} WHML_t + \epsilon_{j,t}. \tag{5}$$

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.

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

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

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 $LSMB$.

[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).

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

$$R_{j,t} = E(R_{j,t}) + \beta_j^{WPC1} WPC1_t + \beta_j^{WPC2} WPC2_t + \beta_j^{WPC3} WPC3_t + \epsilon_{j,t}. \tag{7}$$

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.

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

$$\begin{aligned} R_{j,t} &= E(R_{j,t}) + \beta_j^{WPC1} WPC1_t + \beta_j^{WPC2} WPC2_t + \beta_j^{WPC3} WPC3_t \\ &\quad + \beta_j^{LPC1} LPC1_t + \beta_j^{LPC2} LPC2_t + \beta_j^{LPC3} LPC3_t + \epsilon_{j,t}, \end{aligned} \tag{8}$$

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.

[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.

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

$$R_{j,t} = \alpha_t + D'_{C,j} * C_t + D'_{I,j} * I_t + \epsilon_{i,t}. \tag{9}$$

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, $WMKT_t$. A cross-sectional regression for each period suffices to extract C_t and I_t.

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 effect, I_t, to be zero, then we have a country-effect-only model, and we denote it the DC model (dummy for country). Similarly, if we restrict all country effect, C_t, to be zero, then we have an industry-effect-only model, and we denote it the DI model (dummy for industry). We can derive analogous models for country-style portfolios, and we call them the DCS model (dummy for country and style), the DC model (dummy for country) and the DS model (dummy for 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 end up affecting the industry or factor realizations spuriously. Moreover, the prediction of the dummy variable model for the covariance between asset $j1$ and $j2$ is empirically quite restrictive:

$$cov(R_{j1}, R_{j2}) = cov(WMKT + C_{j1} + I_{j1}, WMKT + C_{j2} + I_{j2}) + cov(\epsilon_{j1}, \epsilon_{j2}). \tag{10}$$

Assuming zero residual covariances, the covariances across firms only depend on country or industry membership. Hence, if we have another firm $j3$ that belongs to the same country and same industry as firm $j1$, then we would have $cov(R_{j1}, R_{j2}) = cov(R_{j3}, R_{j2})$[9].

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

In general, the parameters are re-estimated every six month period, but differences exist for both the APT models and the dummy variable models. The dummy variable models are estimated cross-sectionally every week. For the APT models, we first extract the global and regional factors using Jones's (2001) approach from each six-month period, then factor loadings are estimated.

Table 3 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, while together with region-specific market factors, the R^2 goes up to 37%. The WFF model explains 27% of the total variance, and together with region-specific Fama-French factors, the R^2 increases to 44%. The WAPT model explains 39% by itself, and with the addition of region-specific factors,

[9] The restrictiveness of this approach becomes very apparent if we further assume, as often is done, that the country and industry factors are orthogonal. Then the covariances between stocks are the (partial) sum of the world market variance, the country and/or industry variances.

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 difference in R^2 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^2s. For instance, the difference in R^2 for the WLFF model and the WFF model goes from 25% for 1980-1985 to 11% for 1998-2003. 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.

We use a cross-sectional regression with weekly data to estimate the DCI/DSI model. 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. The average adjusted R^2 for the DCI model is about 38% for country-industry portfolios, and 40% for country-style portfolios.

To help interpret the APT factors, Panel B explores the relation between the APT factors and the FF factors. If we regress the first three global APT factors on the global Fama and French factors every six-month, the time-series average of the adjusted R^2s are respectively 67%, 26% 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, because the time-series averages of the adjusted R^2's when regressing regional APT factors on regional Fama-French factors are only around 10-20%. 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^2s are 81%, 23% and 29%. For the regional Fama-French factors, the R^2s are between 10%-40%. The significant relation between APT factors and Fama-French factors might explain why we usually obtain similar empirical results using the two models, in the later part of the paper.

4.2. Model Selection Outline

Subsections 4.3 through 4.5 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,

$$COV_{sample,t} = \begin{pmatrix} var(R_1) & cov(R_1,R_2) & ... & cov(R_1,R_n) \\ cov(R_1,R_2) & var(R_2) & ... & cov(R_2,R_n) \\ ... & ... & ... & ... \\ cov(R_1,R_n) & cov(R_2,R_n) & ... & var(R_n) \end{pmatrix}. \tag{11}$$

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

$$\begin{aligned} COV_{sample,t} &= \begin{pmatrix} var(R_1) & \beta_{1t}'\Sigma_{F,t}\beta_{2t} & ... & \beta_{1t}'\Sigma_{F,t}\beta_{nt} \\ \beta_{2t}'\Sigma_{F,t}\beta_{1t} & var(R_2) & ... & \beta_{2t}'\Sigma_{F,t}\beta_{nt} \\ ... & ... & ... & ... \\ \beta_{nt}'\Sigma_{F,t}\beta_{1t} & \beta_{nt}'\Sigma_{F,t}\beta_{2t} & ... & var(R_n) \end{pmatrix} \\ &+ \begin{pmatrix} 0 & cov(\epsilon_1,\epsilon_2) & ... & cov(\epsilon_1,\epsilon_n) \\ cov(\epsilon_2,\epsilon_1) & 0 & ... & cov(\epsilon_2,\epsilon_n) \\ ... & ... & ... & ... \\ cov(\epsilon_n,\epsilon_1) & cov(\epsilon_n,\epsilon_2) & ... & 0 \end{pmatrix} \\ &= COV_{\text{model},t} + COV_{\epsilon,t}. \end{aligned} \tag{12}$$

The factor models only have testable implications for covariances, so we make the diagonal elements in $COV_{\text{model},t}$ 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 converge to zero asymptotically. We can define $CORR_{sample,t}$, $CORR_{\text{model},t}$ and $CORR_{\epsilon,t}$ analogously, by dividing each element of all the components in the covariance matrix by $[var(R_i)var(R_j)]^{0.5}$.

From the decomposition, it is straightforward to derive test statistics of model fit. For example, in section 4.3, we investigate the time-series average of a weighted average of the correlation errors:

$$ABSE_{CORR} = \frac{1}{T}\sum_{t=1}^{T}\left(\frac{1}{\overline{W_t}}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,t}w_{j2,t}\left|CORR_{sample,t}(R_{j1,t},R_{j2,t}) - CORR_{\text{model},t}(R_{j1,t},R_{j2,t})\right|\right), \tag{13}$$

where $t = 1,...,T$ refers to different six-month periods, and $\overline{W_t} = \sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,t}w_{j2,t}$, a scalar that makes the weights add up to one, where individual portfolio weights are determined by the portfolio's market capitalization from the previous month. The $ABSE_{CORR}$ statistic intuitively measures the magnitude of the average deviation from the sample correlation. 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 gives an idea of how well the various models fit the correlation matrix and how various features of our factor models affect their ability to match the sample covariance matrix.

In section 4.4, we formally test the performance of each model relative to the other models using a root mean squared error criterion, which is the time series mean of a weighted average of squared errors,

$$RMSE_{CORR} = \{\frac{1}{T}\sum_{t=1}^{T}(\frac{1}{\overline{W_t}}\sum_{j1=1}^{n_{PORT}}\sum_{j2>j1}^{n_{PORT}} w_{j1,t}w_{j2,t}[CORR_{sample,t}(R_{j1,t},R_{j2,t})-CORR_{\text{model},t}(R_{j1,t},R_{j2,t})]^2)\}^{0.5}. \tag{14}$$

Using $ABSE_{CORR}$ for this purpose gives identical results.

Finally, section 4.5 examines how well the best model fits the covariance structure of various subsets of our test portfolios.

4.3. Correlation Errors and the Role of Beta Variation

The average portfolio level correlation in the data is 0.36 for country-industry portfolios and 0.44 for country-style portfolios[10]. Table 4 presents $ABSE_{CORR}$, 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 4, we start with a unit-beta world CAPM model as a benchmark. That is, we take equation (3), and we assume $\beta_{WMKT} = 1$. On average, the unit beta model generates a correlation of only 0.075, leading to an average error of as large as 0.284, since the data correlation is 0.359. We then let the β_{WMKT} take on 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 does not improve the model's ability to match the sample correlations. The magnitude of $ABSE_{CORR}$ is still 93% of that of the unit beta model. The next experiment allows β_{WMKT} to equal the time-series average

[10]This is calculated as the time-series average of $\frac{1}{\overline{W_t}}\sum_{i=1}^{n}\sum_{j>i}^{n} w_{it}w_{jt}CORR_{data,t}(R_{it},R_{jt})$, where $\overline{W_t} = \sum_{i=1}^{n}\sum_{j>i}^{n} w_{it}w_{jt}$, w_{it} and w_{jt} represent weights based on market capitalizations. Using equally-weighted correlations does not affect any of our empirical results.

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 (89% of unit beta model's error), but the average error is still as large as 0.251. If we allow the β_{WMKT} to vary both cross-sectionally and over time, as in the first row of the sixth and seventh columns, the $ABSE_{CORR}$ statistic drops to 0.162, only 57% of the error predicted 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 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 $ABSE_{CORR}$ measure decreases to 0.133 for the WFF model and 0.132 for the WAPT model. If we include regional (local) factors, the $ABSE_{CORR}$ measure drops down to 0.081 for the WLFF model and to 0.076 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 Heston-Rouwenhorst model's $ABSE_{CORR}$ is 0.123, which is lower than the WCAPM's error of 0.162, but higher than that of the WLCAPM model. In conclusion, allowing free loadings on the market portfolios and the regional factors is more effective than including country and industry dummies for matching the correlations. 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-Rouwenhorst 1994, Griffin and Karolyi 1998), a number of relatively recent articles argue that industry factors have become more dominant (see Cavaglia, Brightman and Aked 2000, Baca et al. 2000). The most recent articles provide a more subtle but still conflicting interpretation of the data. Brooks and Del Negro (2004) find that the TMT sector accounts for most of the increasing importance of industry factors and argue that the phenomenon is likely 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[11]. Finally, Carrieri, Errunza and Sarkissian (2004) claim that there has been a gradual increase in the importance of industry factors. From Table 4, we learn that over the full sample, shutting down country dummies leads to an average correlation error of 0.239 (as for the DI model), while shutting down industry dummies leads to an average error of only 0.195 (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.

On a technical level, 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 0.284 error) to a Fama-French or APT model with global and local factors and time-varying betas (an error of 0.076). For example, recently a few papers have modified the Heston-Rouwenhorst approach to allow for non-unitary but time-invariant betas (see Brooks and DelNegro 2003, Marsh and Pfleiderer 1997). 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.

Panel B performs the same computations for country-style portfolios. The results are quite similar. The WLAPT 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.

[11] 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.

4.4. Minimizing RMSE

In this section, we conduct statistical tests to choose the best model for matching the sample correlation matrix over time. Table 5 reports the model comparison results using $RMSE_{CORR}$. Every cell of the matrix presents the t-stat testing the significance of $RMSE(\text{model } i) - RMSE(\text{model } j)$. Standard errors are adjusted using the Newey and West (1987) approach with four lags. Panel A presents results for country-industry portfolios. For example, between WCAPM (model j) and WLCAPM (model i) (third row, second column), the t-stat is -5.00, which indicates that WLCAPM has a significantly lower RMSE 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 ($t = -2.28$), indicating that including the Fama-French factors significantly improves upon the market model. The WLAPT model is significantly better than the WLCAPM ($t = -2.35$), and it is also better than WLFF ($t = -0.31$), 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 one exception. The DCI model is significantly better than WCAPM. We confirm the previous finding that the dummy variable approach cannot generate the covariance structure observed in the data. We also examine the relative importance of country versus industry dummies by comparing the DC and DI models. For country-industry portfolios, DCI (with both country and industry effects) is significantly better than DI ($t = -3.34$), but only marginally better than DC ($t = -1.92$). DC has a lower RMSE than DI, 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 ($t = -3.15$). This is reasonable, given that we have 23 countries, but only nine different styles.

One caution about the results in Table 5 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 observations), we encounter a degrees of freedom problem[12]. To mitigate this problem, we choose subsets of

[12] We estimate sample covariance matrix each period. Since we have 23 countries and 26 industries, the covariance

the country-industry (or country-style) space to examine whether we obtain the same inference. The results are presented in Table 6. The first subset we examine is country-industry portfolios, within the G5 countries, using the most volatile and least volatile industries. This gives us at most 20 portfolios per six-month period. Results presented in Panel A of Table 6 are consistent with our findings using all country-industry portfolios. We next use the country-industry portfolios for the G5 countries, but only for the largest and smallest industries in terms of market capitalization. Panel B presents the results. While the results are generally robust, the WLFF model now becomes better than every other model. However, the improvement of WLFF on WLAPT is neither large nor significant. The last subset we choose for country-industry portfolios are the TMT industries in the G5 countries. Brooks and Del Negro (2002) show that the TMT industries are important in explaining the increase in world market volatility at the end of 1990s. The results are presented in Panel C, and WLAPT is still the best model across the board.

We also conduct the subset experiment for the country-style portfolios. In Panel D, we investigate the G5 countries, and four extreme portfolios (small growth, small value, big growth and big value). WLAPT has a smaller $RMSE$ than all the other models, but the difference is not significant for WLFF and WLCAPM. The second subset experiment, reported in Panel E, uses 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 are possibly less well integrated with the world capital market. This subset allows us to see if the covariance structure is possibly different in segmented markets. There are two interesting findings. First, the WLAPT is still the best model, but the difference between WLAPT and WLFF is now significant. This indicates that WLAPT better captures relevant (global/regional) market-wide forces than WLFF for less integrated markets. The second interesting finding is that the dummy variable model DCI beats 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 WLAPT to be the benchmark model for subsequent analysis. The WLFF model is only slightly

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.

worse than the WLAPT model, so we use it as a robustness check.

4.5. How Good is the Best Model?

In this section, we examine the fit of the WLAPT model over meaningful subsets of the portfolio space, namely countries, industries and styles. To this end, we calculate the covariance ratio matrix, where element (i, j) is calculated as $COV_{\text{model},t}(i, j)/COV_{sample,t}(i, j)$. The covariance ratio represents the proportion of the covariance driven by the common factors. If portfolio covariances are fully explained by common exposures to risk factors, the elements of the covariance ratio matrix should approach one. Table 7 reports these covariance ratios averaged within countries, industries and styles.

Let's first focus on country results. For instance, for the industry portfolios and style portfolios in Canada, the WLAPT model accounts for 93% of the covariances on average. Thus, most of the covariances among Canadian portfolios can be explained by portfolio exposures to common risk factors, and idiosyncratic covariances account for only about 7% of the covariances on average. The same findings apply to most of the developed countries. For the less developed or smaller countries, the percentage of covariances explained by the WLAPT model is around 70-80%. The lowest covariance ratio is recorded by Portugal, a small market that until recently was part of the MSCI Emerging Markets Database.

Industry results are presented in the third and fourth columns. Similar to findings sorted by countries, the covariance between portfolios within one industry can mostly be explained by WLAPT, even for the volatile TMT industries. For 11 of 24 industries, the covariance ratio is 90% or higher; only one industry features a covariance ratio of less than 70% (oil and gas). The last three columns report covariance ratios for the different styles. The covariance ratios here are invariably very high, always exceeding 90%. There is no particular style dimension for which the WLAPT model performs poorly.

5. Implications for Comovements

We have now derived a simple risk model that captures the stock return comovements of country-industry and country-style portfolios remarkably well. In this section, we use our time-varying estimates of 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 1980-2003 period. 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. Trends in comovements

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

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

with $\overline{W_t} = \sum_{j1=1}^{n_{PORT}} \sum_{j2=1,j1\neq j2}^{n_{PORT}} w_{j1,t} w_{j2,t}$, a scalar that makes the weights add up to one. We can examine the time series properties of $\gamma^{COV}_{sample,t}$ to understand whether there is a permanent increase or decrease in the sample covariances. We can also decompose $\gamma^{COV}_{sample,t}$ into $\gamma^{COV}_{risk,t}$ and $\gamma^{COV}_{idio,t}$, and examine whether a possible trend is driven by the risk or idiosyncratic components (or model misspecification). Analogously, we can define the same decomposition for correlations, where

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

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[13]. 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. Neither sample correlations display any obvious trends. We present γ^{CORR}_{risk} and γ^{CORR}_{idio} decomposition in Panels B and C. 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

[13] We choose to present the γ^{CORR} rather than γ^{COV} measures because they are more easily interpretable.

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), and visually there are no obvious time trends. Because of the close fit between model and data, we do not further report statistics regarding idiosyncratic comovements.

Vogelsang (1998) introduces a simple linear time trend test, which has been widely used in the literature[14]. The benchmark model is defined to be

$$y_t = \alpha_0 + \alpha_1 t + u_t, \tag{17}$$

where y_t is the variable of interest, and t is a linear time trend. Vogelsang (1998) provides a PS1-stat for testing the hypothesis of $\alpha_1 = 0$. The test statistic is robust to $I(0)$ and $I(1)$ error terms. Vogelsang (1998) also provides a 90% confidence interval for α_1.

Table 8 contains our main results. We report statistics for both country-industry portfolios in Panel A and country-style portfolios in Panel B for the correlation measure. Results for the covariance measures are qualitatively identical. We investigate the sample and model comovement measures and two alternative measures, computed by either setting the loadings B_{jt} or the factor covariance matrix, Σ_{Ft} 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 five statistics: the sample average, the sample standard deviation, the correlation between the particular (restricted model or unrestricted model) measure and the data measure and the upper and lower bounds of the 90% confidence intervals for Vogelsang's sample time trend coefficient.

Let's start with the trend results. Whenever we consider all country-industry portfolios or all country-style portfolios, the lower bounds of the 90% confidence interval for both the sample and model correlation measures are always negative, and the upper bounds are always positive. Thus, we do not find a significant time trend in correlations for the base portfolios. There are no trends

[14] 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.

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 0.36, but it shows relatively large time-variation, as its volatility is 0.14. 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.

The most important evidence regarding the restricted measures is their correlation with the sample measures. When factor variance dynamics are kept constant, the correlation measure shows negative correlations with its sample counterpart; whereas time-invariant betas lead to correlations of 92% for the correlation measure. Clearly, though we have demonstrated time-series variation in betas to be an important dimension in the fit of comovements, factor variance dynamics are relatively more important.

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

Table 9 contains our main empirical results. We consider different 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.

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 not involving the Far East, but they are far from statistically significant.

Second, we examine the sources of the trends by either fixing the betas or covariances at their sample averages. We present the results for all countries in Panel B, and for European countries in Panel C. It is unsurprising not to see any significant trends for all countries. Nevertheless, for European decompositions, the trend coefficient is slightly negative when the betas are fixed. Consequently, the upward trend in within-Europe correlations is likely caused by changes in betas, confirming results in Baele (2005) and suggesting the increase in correlations may well be permanent.

Because the risk model incorporates both global and regional factors, it is interesting to 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 0.85 with a positive trend, while by fixing only global betas, the correlation drops to 0.75 and the positive trend disappears. Even though both trend tests do not yield significance, this analysis suggests that the global betas account for the positive 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, when we investigate a time-series plot of the correlations (unreported), 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.

In Table 10, we use the risk model to construct a country-specific measure of integration: the proportion global factors explain of the total explained variance (both global and local factors). Averaged over the whole sample, the proportion varies between 49% for New Zealand and 84% for the Netherlands. That the Netherlands is one of the more "integrated" countries is not surprising given that its stock market is dominated by a few large multi-national companies. The rather segmented status of New Zealand, and also Australia and Canada may have something to do with the industrial composition of those stock markets, in particular the large weight on resources. We will see later that mining and oil and gas are among the least integrated industries. That smaller countries, such as Greece and Singapore, show a low degree of integration is not surprising, but the low value for the US definitely is. Of course, it is the case that the North-America regional factor is completely dominated by the US market.

Finally, the time-variation in the measure is also inconsistent with a smooth globalization process. For some countries, such as France and Greece, the integration measure steadily increases over time but for Japan and Denmark, it steadily decreases and for many countries there is no clear trend at all.

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 11 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 0.62, 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 only 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 slightly positive, it is not significantly different from zero. The decomposition suggests that the positive coefficient is likely due to changing factor variances. Again, excluding the TMT sector does not alter these conclusions. The most important conclusion is 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 90's, 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 11. 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 and significant trend. The decomposition also reveals the main reason behind the trend: it comes from an increase in factor volatilities during the short sample period. We know factor volatilities do not exhibit trends over longer periods.

Finally, Table 12 examines whether the degree of integration varies across industries by computing the variance explained by global factors relative to the total explained variance. The least integrated industry is mining followed by oil and gas. While these are industries affected by global commodity prices, they also may be more likely to be regulated by local authorities. Surprisingly, the utility sector is not less integrated than the TMT sector. The most integrated industries over the whole sample were machinery and construction. Overall, the differences in the degree of integration between different industries are much less marked than the difference between countries. This is simply a reflection of the fact that industry portfolios represent portfolios that are well-diversified across countries, and as we saw above, country factors still dominate. A number of industries have become less integrated over time, including chemicals, construction, steel machinery, food, health, retail, transport, and defense. The opposite is not really observed.

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 led correlations of large stocks to be increasingly higher across countries 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 13. Panel A demonstrates that the correlations among small stocks are indeed lower than those among large stocks, by about 0.08. 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. However, we do not see any evidence of a trend over time, and the estimated trend coefficient is slightly negative. Panel B of Table 13 shows that the correlation among growth and value stocks is about the same at 0.34. However, the trend coefficient for the correlation difference, while not statistically significantly different from zero, is rather large and 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. In Panel C of Table 13, 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. While both changes in beta and factor covariances contribute to the positive trend, the dominant effect appears to come from betas. 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 $\gamma_{idio,t}^{CORR}$ 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,

$$\begin{aligned} \sigma_{sample,t}^2 &= \sum_{j=1}^{n} w_{j,t} var(R_{j,t}) \\ &= \sum_{j=1}^{n} w_{j,t} var(\beta_j' F_t) + \sum_{j=1}^{n} w_{j,t} var(\epsilon_{j,t}) \\ &= \sigma_{risk,t}^2 + \sigma_{idio,t}^2, \end{aligned} \tag{18}$$

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. This is also clear from a plot of the different variance measures in Figure 3. 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 the following section, we

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

revisit the issue with firm level data.

6. Firm Level Evidence

While thus far our results use country-industry and country-style portfolios, we now investigate our model's implication for individual firms. In section 6.1, we examine whether the model implies a realistic correlation structure for several representative firms. In section 6.2, we examine the time-series properties of idiosyncratic volatility at the firm level.

6.1. Model Implied Correlation for Example Firms

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, with the emphasis on country and industry effects. To calculate the WLAPT model implied correlation for every six-month period, we first estimate the factor loadings for the four firms. The implied covariance is then calculated as in equation (2). To calculate the dummy variable models implied correlation 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 (10). Consequently, we apply the model, derived for country-industry portfolios or country-style portfolios, in an "out-of-sample" experiment with firm level data.

Table 14 reports the sample covariances and correlations of the firm returns, and the implied covariances and correlations from the WLAPT model and 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 WLAPT model generates a covariance that is low and reaches about 71% of the sample covariance on average. The DCI and DCS models on average still underestimate the sample covariance but reach about over 82% of the sample covariance. However, the covariances generated by the WLAPT model correlate over time much more highly with the sample covariances than the covariances produced by the DCI and DCS models. Hence, the WLAPT model better matches comovement dynamics between Novartis and Merck. The statistics for correlation measures show a similar pattern.

We also examine another three pairs, Nihon Unisys and IBM, Merck and IBM, and Novartis and IBM. The advantage of the WLAPT model over the DCI/DCS models is now dramatic in terms of matching both the magnitude and the time-series dynamics of comovements. The correlation between the model and sample comovements is at least 73% for the WLAPT model but never reaches 50% for the dummy variable models. For example, the DCI model strikingly over-predicts the comovements between the two info tech firms and the two American firms, whereas the WLAPT produces a very realistic correlation and covariance number. The above exercises indicate that the dummy variable approach is not flexible enough to capture firm level comovements, while the WLAPT model performs very well for this set of firm returns.

6.2. Is there a trend in firm level volatility measure?

Campbell, Lettau, Malkiel and Xu (2001, CLMX[16] hereafter) explore the time-series dynamics of idiosyncratic risk at the firm level in the United States. To estimate idiosyncratic risk, CLMX perform the following decomposition for firm j's return,

$$\begin{aligned} R_{j,t} &= R_{MKT,t} + (R_{IND,t} - R_{MKT,t}) + (R_{j,t} - R_{IND,t}) \\ &= R_{MKT,t} + \epsilon_{IND,t} + \epsilon_{j,t}, \end{aligned} \tag{19}$$

where $R_{MKT,t}$ is the excess return on the market portfolio, $R_{IND,t}$ is the excess return of the industry portfolio to which firm j belongs. CLMX refer to the term $\epsilon_{IND,t}$ as the industry-specific return, and to $\epsilon_{j,t}$ as the firm-specific return. The advantage of equation (19) is that it leads to the following simple variance decomposition for an average firm:

$$\begin{aligned} \sum_{j=1}^{n_{FIRM}} w_j var(R_{j,t}) &= var(R_{MKT,t}) + \sum_{k=1}^{n_{IND}} w_{IND,k} var(\epsilon_{IND,k,t}) + \sum_{j=1}^{n_{FIRM}} w_j var(\epsilon_{j,t}) \\ &= \sigma^2_{MKT,t} + \sigma^2_{IND,t} + \sigma^2_{FIRM,t}, \end{aligned} \tag{20}$$

where n_{FIRM} is the number of firms within the US, w_j is the weight for firm j, n_{IND} is the number of industries within the US, $w_{IND,k}$ is the weight for industry k, $\sigma^2_{MKT,t}$ is the variance for the market portfolio, $\sigma^2_{IND,t}$ is the industry specific variance and $\sigma^2_{FIRM,t}$ is the firm specific or idiosyncratic variance. Obviously, the disadvantage of the CLMX model is that it assumes the

[16] The PS1 stat reported in Campbell, Lettau, Malkiel and Xu (2001) is mislabelled. The numbers are actually the parameter estimate of α_1.

loadings of all firms on the market portfolio and the relevant industry portfolios to be one. CLMX's article has generated much attention because it documents a positive and significant trend in the firm level variance[17].

Here we re-examine the CLMX evidence using weekly firm-level returns from 23 different countries for our 1980-2003 period. To conserve space, we only report the results for the G7 countries in Panel A of Table 15. We calculate the variance decomposition as in equation (20) for CLMX approach and equation (18) from our WLAPT model. We then compare the average firm level variance measures, CLMX's σ^2_{firm} and our σ^2_{idio}, and examine whether there is a time-trend in these two measures. Table 15 provides the results for Vogelsang's linear trend test. Panel A presents the time trend estimate and its 90% confidence interval for σ^2_{firm} and σ^2_{idio}. Over the sample period 1981-2003, only France's firm level idiosyncratic variances show a positive time trend for σ^2_{firm}. The positive trend in France's idiosyncratic variance measure disappears and there is no trend for any other countries, when we switch to σ^2_{idio}. Consequently, there is no strong statistical evidence in favor of a trend in idiosyncratic variances. Nevertheless, the trend coefficient is positive for all 7 countries. However, when we investigate trends in the 16 other countries, not only do we never reject the null of no trend, the trend coefficient is negative in 9 out of the 16 cases. The assumption of a unit beta turns two out of the negative coefficients into positive coefficients.

In Panel B, we restrict our sample period to be consistent with CLMX's original sample period, 1964-1997, using only US firms daily returns. We find a significant and positive trend over CLMX's sample period of 1964-1997[18]. However, for any other combinations such as 1981-1997, 1981-2003, 1964-2003, we fail to find a trend. While it is striking that the trend coefficient increases in every case when going from σ^2_{firm} to σ^2_{idio}, it seems clear that the CLMX result is simply due to the particular sample period. Consequently, our results are consistent with recent results for the US stock market by Brandt et al (2005) and cast doubt on the many efforts to "explain" the trend in idiosyncratic behavior.

[17] Ferreira and Gama (2005) adopt CLMX's methodology and apply it to country-industry portfolios. They find no evidence of a trend in the idiosyncratic variance at the local industry portfolio level.

[18] CLMX uses daily returns, so we also replicate their results using daily returns. The results are very similar to what we find for weekly returns.

7. 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 allowing risk sources other than the market. We also allow the risk loadings on the factors to vary cross-sectionally and over time.

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.

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.

Finally, we show that the intriguing evidence in CLMX (2001), suggesting that the idiosyncratic variance of firm-level returns has trended upward, is specific to the sample period used and does not extend to 22 other countries.

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Table 1. Summary statistics for the firm returns

The sample period is January 1980 to December 2003. 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. The numbers reported are time-series average relevant statistics.

	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	18.09%	621	1.00	379	247	2.1%
FRANCE	198001	17.62%	841	1.07	380	422	2.6%
GERMANY	198001	10.71%	944	0.72	438	450	3.3%
ITALY	198001	18.95%	1056	1.04	169	205	1.3%
JAPAN	198001	14.67%	1543	0.69	1426	2308	23.7%
UNITED KINDOM	198001	16.76%	799	0.93	1069	981	8.3%
UNITED STATES	198001	16.45%	940	0.82	3977	5482	50.1%
AUSTRALIA	198001	18.68%	596	1.02	299	166	1.3%
AUSTRIA	198001	13.10%	181	1.29	57	14	0.1%
BELGIUM	198001	16.80%	489	1.46	78	53	0.3%
DENMARK	198001	17.20%	232	1.22	129	36	0.2%
FINLAND	198701	15.69%	651	0.73	88	79	0.4%
GREECE	198801	26.39%	183	0.78	173	40	0.2%
HONG KONG	198001	21.13%	785	1.27	240	195	1.4%
IRELAND	198001	21.30%	464	1.14	38	23	0.1%
NETHERLANDS	198001	16.34%	1586	1.27	115	229	1.6%
NEW ZEALAND	198601	14.62%	386	0.99	46	14	0.1%
NORWAY	198001	18.15%	285	0.96	94	28	0.2%
PORTUGAL	198801	11.47%	419	1.24	58	30	0.2%
SINGAPORE	198001	17.91%	360	0.93	118	51	0.3%
SPAIN	198601	16.66%	1579	0.96	105	182	1.1%
SWEDEN	198001	17.45%	524	0.99	167	111	0.6%
SWITZERLAND	198001	10.42%	1013	1.12	172	251	1.5%

Table 2. Match SIC industry classification with FTSE industry classification

DataStream provides FTSE level 4 industries, and French 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

Table 3. Factor model estimation results

The sample period is January 1980 to December 2003. 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 global market portfolio return (WMKT), global SMB (WSMB), and global HML (WHML). 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 relevant global factors. Model DCI/DCS is the dummy variable approach from Heston and Rouwenhorst (1994). 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, we first estimate them over weekly data in cross-section. 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 for 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 time-series average of the adjusted R-square of regressing individual Fama-French factors on different APT factors.

Panel A. Adjusted R^2's

	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI/DCS
Country-industry portfolios							
whole sample	23%	37%	27%	44%	39%	54%	38%
80-85	31%	51%	35%	60%	54%	69%	43%
86-91	25%	40%	28%	47%	41%	57%	36%
92-97	16%	28%	17%	33%	30%	44%	35%
98-03	21%	28%	26%	37%	32%	44%	37%
Country-style portfolios							
whole sample	21%	33%	27%	45%	41%	56%	40%
80-85	28%	46%	34%	60%	53%	70%	43%
86-91	21%	33%	26%	44%	41%	57%	37%
92-97	14%	25%	17%	36%	34%	49%	39%
98-03	21%	29%	30%	42%	38%	50%	42%

Panel B. APT factors vs. Fama-French factors

	Independent Variables	Dependent variables			Independent Variables	Dependent variables		
		PC1	Variables	PC3		MKE	SMB	HML
global	WFF	67%	26%	19%	WAPT	81%	23%	29%
North America	WFF	12%	16%	15%	WAPT	33%	9%	10%
	LFF	21%	11%	11%	LAPT	30%	11%	12%
Europe	WFF	11%	8%	7%	WAPT	45%	7%	6%
	LFF	13%	14%	11%	LAPT	16%	9%	10%
Far East	WFF	9%	7%	7%	WAPT	41%	11%	9%
	LFF	20%	16%	12%	LAPT	23%	11%	10%

Table 4. Model fit: the role of betas and multiple factors

The sample period is January 1980 to December 2003. All 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 global market portfolio return (WMKT), global SMB (WSMB), and global HML (WHML). Model WAPT is the global APT model with three factors. Models WLCAPM, WLFF and WLAPT include both local and global factors, with the local factors constructed over regional markets and orthogonalized to the relevant global factors. 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. The ABSE measure is 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) portfolios. Free beta means there are no restrictions.

Panel A: Country-industry portfolios

	Unit beta	Cross-section average beta		Time-series average beta		Free beta	
	ABSE	ABSE	% of unit beta ABSE	ABSE	% of unit beta ABSE	ABSE	% of unit beta ABSE
WCAPM	0.284	0.262	93%	0.251	89%	0.162	57%
WLCAPM		0.263	93%	0.220	78%	0.108	38%
WFF		0.263	93%	0.253	89%	0.133	47%
WLFF		0.265	93%	0.221	78%	0.081	28%
WAPT		0.270	95%	0.370	131%	0.132	47%
WLAPT		0.274	96%	0.364	128%	0.076	27%
DCI						0.123	43%
DI						0.239	84%
DC						0.195	69%

Panel B: country-style portfolios

	Unit beta	Cross-section average beta		Time-series average beta		Free beta	
	ABSE	ABSE	% of unit beta ABSE	ABSE	% of unit beta ABSE	ABSE	% of unit beta ABSE
WCAPM	0.292	0.295	101%	0.273	93%	0.171	58%
WLCAPM		0.289	99%	0.218	75%	0.090	31%
WFF		0.280	96%	0.276	94%	0.146	50%
WLFF		0.276	94%	0.218	75%	0.064	22%
WAPT		0.289	99%	0.435	149%	0.126	43%
WLAPT		0.288	99%	0.428	146%	0.062	21%
DCS						0.099	34%
DS						0.286	98%
DC						0.123	42%

Table 5. Model fit: matching the sample portfolio correlation matrix

The sample period is January 1980 to December 2003. 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), global SMB (WSMB), and global HML (WHML). 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 is the restricted dummy variable model with only industry dummies. Model DC is the restricted dummy variable model with only country dummies. Every cell (i,j) reports the t-stat for RMSE(model i)-RMSE(model j). The statistic RMSE is defined in equation (14). The standard errors accommodate 4 Newey-West (1987) lags.

Panel A: country-industry portfolio correlation matrix

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-5.00							
WFF	-2.80	0.93						
WLFF	-3.78	-2.28	-5.00					
WAPT	-3.36	1.31	-0.03	2.79				
WLAPT	**-3.97**	**-2.35**	**-5.42**	**-0.31**	**-3.07**			
DCI	-2.05	2.81	1.47	2.77	1.86	2.90		
DI	3.17	3.78	3.57	3.93	3.67	4.00	3.53	
DC	1.69	2.12	1.86	2.15	2.02	2.17	1.92	-0.34

Panel B: country-style portfolio correlation matrix

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-5.37							
WFF	-3.91	5.44						
WLFF	-5.14	-3.77	-5.44					
WAPT	-2.90	2.50	-1.59	3.70				
WLAPT	**-5.64**	**-3.68**	**-6.03**	**-0.17**	**-4.66**			
DCS	-2.00	1.74	-0.40	2.19	0.78	2.44		
DS	2.88	3.43	3.15	3.54	3.31	3.59	3.34	
DC	-0.25	1.87	0.62	2.16	1.43	2.31	1.92	-3.15

Table 6. Model fit: robustness check using subsets of test portfolios

The sample period is January 1980 to December 2003. 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), global SMB (WSMB), and global HML (WHML). 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 is the restricted dummy variable model with only industry dummies. Model DC is the restricted dummy variable model with only country dummies. Every cell (i,j) reports the t-stat for RMSE(model i)-RMSE(model j). The statistic RMSE is defined in equation (14). The standard errors accommodate 4 Newey-West (1987) lags.

Panel A: Correlation matrix for G5 countries, least volatile industries (food and utility) and most volatile industries (info tech and electronics)

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-4.10							
WFF	-5.67	0.98						
WLFF	-6.77	-7.21	-5.39					
WAPT	-3.17	1.35	0.20	6.00				
WLAPT	-6.58	-4.56	-4.83	-0.25	-7.56			
DCI	-0.99	2.96	1.95	5.11	1.85	6.44		
DI	3.57	3.93	4.47	4.79	3.99	4.87	3.35	
DC	4.01	5.46	4.79	6.14	5.02	6.51	4.70	0.97

Panel B: Correlation matrix for G5 countries, smallest industries (household and recreation) and biggest industries (finance and oil and gas)

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-3.97							
WFF	-5.44	1.45						
WLFF	-6.38	-4.46	-3.98					
WAPT	-1.49	1.81	0.36	4.19				
WLAPT	-4.97	-1.84	-2.88	0.38	-6.18			
DCI	-2.98	0.52	-0.60	1.75	-0.79	1.71		
DI	4.85	5.09	5.66	5.77	4.29	5.29	5.10	
DC	1.27	3.38	2.10	3.85	2.46	4.34	2.57	-2.19

Panel C: Correlation matrix for G5 countries, TMT industries (Telecom, Media and Info Tech)

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-3.08							
WFF	-3.92	1.84						
WLFF	-3.78	-3.82	-2.90					
WAPT	-1.10	3.02	0.57	4.18				
WLAPT	-3.80	-2.60	-3.01	-0.56	-5.73			
DCI	-2.12	2.38	-0.79	3.72	-1.82	4.52		
DI	5.04	5.78	6.97	6.57	4.51	6.08	5.20	
DC	0.90	3.67	1.97	4.18	1.92	4.89	2.96	-1.05

Panel D: Correlation matrix for G5 countries, small growth, small value, big growth and big value portfolios

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-5.12							
WFF	-3.32	3.98						
WLFF	-5.95	-4.16	-5.38					
WAPT	-3.51	1.83	-2.30	5.69				
WLAPT	-4.90	-1.72	-4.14	-0.33	-5.40			
DCI	-3.90	-0.06	-2.73	1.56	-1.73	3.43		
DI	5.42	6.54	6.56	6.98	6.01	6.34	5.55	
DC	-2.54	0.99	-1.57	2.68	-0.17	5.98	2.88	-4.89

Panel E: Correlation matrix for Far East countries (Australia, Hong Kong, New Zealand, Singapore), small growth, small value, big growth and big value portfolios

t-stat	Model j							
Model i	WCAPM	WLCAPM	WFF	WLFF	WAPT	WLAPT	DCI	DI
WLCAPM	-3.53							
WFF	-4.49	-4.00						
WLFF	-4.82	-4.80	-4.07					
WAPT	-4.48	-4.39	-3.75	-1.39				
WLAPT	-5.34	-5.46	-5.28	-5.04	-5.19			
DCI	-3.62	-3.49	-3.05	-2.36	-1.99	2.14		
DI	1.85	2.10	2.47	3.09	3.27	3.98	3.41	
DC	-3.43	-3.27	-2.83	-2.09	-1.75	2.09	0.84	-3.34

Table 7. Covariance ratios for the WLAPT model

The sample period is January 1980 to December 2003. All the returns are denominated in US dollar. Presented numbers are average covariance ratio, $COV_{model}./COV_{sample}$, with COV_{sample} to be the sample covariance, and COV_{model} to be the covariance predicted by the WLAPT model, and the division ./ is conducted element by element. The covariance ratios are averaged over time, then averaged over styles, industries and countries.

country	cov ratio	industry	cov ratio	size	BM	cov ratio
CANADA	93%	mining	72%	small	low	100%
FRANCE	89%	oil and gas	56%	small	median	93%
GERMANY	89%	chemical	96%	small	high	96%
ITALY	86%	construction	98%	median	low	96%
JAPAN	96%	forestry	75%	median	median	97%
UK	83%	steel	80%	median	high	97%
US	93%	electronics	96%	big	low	94%
AUSTRALIA	87%	machinery	99%	big	median	94%
AUSTRIA	68%	automobiles	86%	big	high	95%
BELGIUM	74%	household	92%			
DENMARK	72%	food	90%			
FINLAND	79%	health	81%			
GREECE	82%	wholesale	94%			
HONG KONG	88%	retail	88%			
IRELAND	79%	recreation	98%			
NETHERLANDS	93%	**media**	**95%**			
NEW ZEALAND	71%	transport	82%			
NORWAY	70%	**telecom**	**74%**			
PORTUGAL	66%	utility	74%			
SINGAPORE	84%	finance	86%			
SPAIN	75%	defense	88%			
SWEDEN	84%	diversified	100%			
SWITZERLAND	81%	service	98%			
		info tech	**87%**			

Table 8. Long-term movements in correlations: base portfolios

The sample period is January 1980 to December 2003. We report characteristics of 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, correlation with data, and the 90% confidence interval (lower bound and upper bound) from Vogelsang's trend test.

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	36%	36%	50%	44%
std. dev.	13%	13%	18%	12%
correl(.,data)	100%	100%	-14%	92%
lower	-0.936	-0.946	-1.782	-0.745
upper	0.226	0.227	1.054	0.209

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	44%	44%	64%	51%
std. dev.	14%	14%	21%	13%
correl(.,data)	100%	100%	-21%	89%
lower	-1.070	-1.054	-2.210	-0.557
upper	0.707	0.696	1.611	0.581

Table 9. Long term movements in country return correlations

The sample period is January 1980 to December 2003. We aggregate the base portfolios into several subgroups and also investigate bivariate correlation relative to the US country return. We report characteristics of γ^{CORR}_{sample} and its model counterpart, γ^{CORR}_{risk}, as in equation (16). In Panel B and C, we examine three versions of γ^{CORR}_{risk}. 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, correlation with data, and the 90% confidence interval (lower bound and upper bound) from Vogelsang's trend test.

Panel A. Correlations

	γ^{CORR}_{sample} mean	trend lower	upper	γ^{CORR}_{risk} mean	trend lower	upper
all countries	37%	-0.763	1.258	37%	-0.730	1.243
G7	37%	-0.827	1.272	37%	-0.801	1.265
Europe	54%	0.177	0.983	60%	0.039	0.732
Far East	30%	-1.377	1.226	34%	-1.374	1.401
US vs. Far East	27%	-0.662	0.483	27%	-0.643	0.477
US vs. Europe	39%	-0.978	1.748	39%	-0.991	1.763
US vs. all other countries	35%	-0.966	1.436	35%	-0.949	1.433

Panel B. All countries

	γ^{CORR}_{sample}	γ^{CORR}_{risk}	γ^{CORR}_{risk}	γ^{CORR}_{risk}
Beta		Free	Free	TSA
Factor cov		Free	TSA	Free
mean	37%	37%	53%	46%
std. dev.	16%	16%	20%	15%
correl(.,data)	100%	100%	-6%	91%
lower	-0.763	-0.730	-1.396	-0.385
upper	1.258	1.243	1.933	1.023

Panel C. European countries

	γ^{CORR}_{sample}	γ^{CORR}_{risk}	γ^{CORR}_{risk}	γ^{CORR}_{risk}
Beta		Free	Free	TSA
Factor cov		Free	TSA	Free
mean	54%	60%	86%	71%
std. dev.	16%	14%	26%	12%
correl(.,data)	100%	98%	13%	72%
lower	0.177	0.039	-1.791	-0.585
upper	0.983	0.732	4.282	0.566

Table 10. Country specific measures of capital market integration

The sample period is January 1980 to December 2003. All the returns are denominated in US dollar. We report the ratio of the variance explained by global factor over the variance explained by both global and local factors, using the WLAPT model. For the first subperiod 1981-1986, we only report results for 6 countries, because other countries do not have complete time series data when we require the country has 9 style portfolios with each portfolio with at least 15 firms.

	whole sample	1981-1986	1987-1992	1993-1998	1999-2003
CANADA	61%	70%	49%	57%	70%
FRANCE	75%	62%	74%	77%	87%
GERMANY	82%	70%	87%	83%	87%
ITALY	81%		78%	80%	86%
JAPAN	74%	84%	82%	67%	59%
UK	83%	88%	77%	82%	82%
US	65%	81%	54%	54%	71%
AUSTRALIA	53%		47%	60%	57%
AUSTRIA	75%		75%	76%	70%
BELGIUM	82%		82%	81%	82%
DENMARK	79%		84%	78%	73%
FINLAND	76%		62%	81%	79%
GREECE	65%		53%	58%	73%
HONG KONG	68%		62%	74%	71%
IRELAND	68%		62%	73%	71%
NETHERLANDS	84%		82%	84%	88%
NEW ZEALAND	49%		56%	55%	42%
NORWAY	75%		73%	74%	78%
PORTUGAL	77%		72%	76%	77%
SINGAPORE	61%		57%	62%	61%
SPAIN	83%		84%	81%	83%
SWEDEN	81%		75%	79%	89%
SWITZERLAND	83%		89%	77%	83%

Table 11. The country-industry debate

The sample period is January 1980 to December 2003. We aggregate the base portfolios into several subgroups. We report characteristics of 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, correlation with data, and the 90% confidence interval (lower bound and upper bound) from Vogelsang's trend test.

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	62%	63%	94%	71%	63%	64%	97%	72%
std. dev.	13%	13%	27%	11%	13%	13%	27%	11%
correl(.,data)	100%	100%	-7%	89%	100%	100%	-9%	91%
lower	-0.638	-0.624	-9.589	-0.249	-2.129	-2.391	-94.561	-1.066
upper	0.518	0.515	10.454	0.360	1.513	1.662	93.022	0.676

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	-25%	-25%	-42%	-25%	-26%	-26%	-45%	-26%
std. dev.	15%	15%	22%	13%	15%	15%	22%	13%
correl(.,data)	100%	100%	77%	89%	100%	100%	76%	89%
lower	-3.301	-2.975	-8.135	-1.057	-3.264	-3.425	-6.886	-1.190
upper	3.922	3.600	8.105	1.575	3.817	4.061	6.718	1.698

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	-21%	-22%	-45%	-23%	-23%	-23%	-47%	-23%
std. dev.	20%	20%	30%	17%	20%	20%	31%	17%
correl(.,data)	100%	100%	87%	92%	100%	100%	87%	91%
lower	1.160	1.209	-3.925	0.816	1.573	1.474	-4.019	0.673
upper	4.235	4.132	15.727	2.890	3.694	3.994	15.633	3.158

Table 12. Industry specific measures of integration

The sample period is January 1980 to December 2003. All the returns are denominated in US dollar. We report the ratio of the variance explained by global factors over the variance explained by both global and local factors, using the WLAPT model.

	whole sample	1981-1986	1987-1992	1993-1998	1999-2003
mining	55%	57%	48%	55%	61%
oil and gas	61%	57%	65%	61%	57%
chemical	75%	83%	77%	72%	66%
construction	77%	87%	77%	72%	68%
forestry	67%	77%	65%	67%	58%
steel	75%	84%	78%	70%	63%
electronics	71%	70%	76%	65%	73%
machinery	78%	86%	81%	71%	70%
automobiles	71%	74%	73%	66%	69%
household	72%	78%	75%	66%	67%
food	72%	84%	72%	65%	56%
health	68%	77%	69%	61%	57%
wholesale	63%	60%	63%	64%	64%
retail	70%	81%	68%	66%	60%
recreation	71%	83%	71%	61%	67%
media	73%	80%	70%	67%	78%
transport	73%	80%	77%	70%	63%
telecom	67%	71%	65%	65%	65%
utility	70%	79%	76%	64%	50%
finance	73%	76%	76%	68%	68%
defence	69%	86%	65%	63%	56%
diversified	68%	74%	68%	67%	62%
service	72%	76%	73%	68%	71%
info tech	69%	72%	64%	62%	78%

Table 13. Long term movements in style return correlations

The sample period is January 1980 to December 2003. We aggregate the base portfolios into several subgroups. We report characteristics of γ^{CORR}_{sample} and its model counterpart, γ^{CORR}_{risk}, as in equation (16). We examine three versions of γ^{CORR}_{risk}. 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, correlation with data, and the 90% confidence interval (lower bound and upper bound) from Vogelsang's trend test.

Panel A. style small versus style big

	small	big	small-big			
	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{risk}	γ^{CORR}_{risk}	γ^{CORR}_{risk}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	37%	45%	-8%	-8%	9%	-7%
std. dev.	15%	14%	15%	15%	24%	14%
correl(.,data)	100%	100%	100%	100%	63%	90%
lower	-2.194	-1.263	-5.005	-5.081	-4.511	-1.746
upper	-0.509	-0.240	4.467	4.493	3.290	0.838

Panel B. style growth versus style value

	growth	value	growth-value			
	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{risk}	γ^{CORR}_{risk}	γ^{CORR}_{risk}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	34%	34%	1%	0%	0%	3%
std. dev.	15%	14%	11%	11%	17%	11%
correl(.,data)	100%	100%	100%	100%	12%	54%
lower	-0.873	-0.577	-0.098	-0.063	-0.455	-0.450
upper	0.150	-0.072	0.543	0.520	1.302	0.340

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

	big growth	small value	big growth – small value			
	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{sample}	γ^{CORR}_{risk}	γ^{CORR}_{risk}	γ^{CORR}_{risk}
Beta				Free	Free	TSA
Factor cov				Free	TSA	Free
mean	33%	23%	10%	9%	3%	10%
std. dev.	16%	14%	14%	14%	18%	13%
correl(.,data)	100%	100%	100%	99%	37%	74%
lower	-0.769	-0.797	**0.099**	**0.144**	**0.235**	**0.062**
upper	0.256	-0.240	**0.894**	**0.914**	**1.413**	**0.677**

Table 14. Firm level comovements

The sample period is January 1980 to December 2003. All the returns are denominated in US dollars. Model WLAPT is a APT model with factors from both the global and regional markets. Model DCI/DCS is the dummy variable model from Heston and Rouwenhorst (1994).

	Covariance (in %)	% of sample cov	Correl (sample cov, model cov)	correlation	% of sample correl	Correl (sample correl ,model correl)
Norvatis and Merck						
data	0.0364			26%		
WLAPT	0.0259	71%	85%	19%	71%	74%
DCI	0.0319	88%	74%	23%	87%	62%
DCS	0.0298	82%	49%	21%	79%	29%
Nihon Unisys and IBM						
data	0.0199			8%		
WLAPT	0.0204	103%	82%	8%	104%	74%
DCI	0.0759	381%	46%	30%	387%	44%
DCS	0.014	71%	52%	7%	87%	44%
Merck and IBM						
data	0.0271			24%		
WLAPT	0.0297	110%	82%	25%	105%	80%
DCI	0.0486	180%	49%	40%	169%	48%
DCS	0.0554	205%	22%	44%	182%	33%
Novartis and IBM						
data	0.0126			11%		
WLAPT	0.0137	109%	73%	11%	103%	83%
DCI	0.0196	155%	29%	13%	116%	41%
DCS	0.0308	244%	23%	19%	177%	42%
Merck and Nihon Unisys						
data	0.0104			6%		
WLAPT	0.0076	73%	67%	5%	77%	63%
DCI	0.0172	165%	23%	9%	133%	30%
DCS	0.0160	154%	35%	7%	113%	42%
Novartis and Nihon Unisys						
data	0.0156			9%		
WLAPT	0.0078	50%	81%	6%	68%	81%
DCI	0.0132	85%	76%	7%	75%	69%
DCS	0.0210	135%	66%	10%	110%	59%

Table 15. Time series behavior of firm level idiosyncratic variance measures

For Panel A, the sample period is January 1980 to December 2003. 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. Firm level variance using the CLMX methodology, CLMX σ^2_{firm}, is defined in equation (20), and the firm level idiosyncratic variance using WLAPT, σ^2_{idio}, is defined in equation (18). Reported are the Vogelsang trend estimates and their 90% confidence interval (all trends are multiplied by 100)

Panel A. Idiosyncratic variances in the G7 countries

	CA	FR	GE	IT	JP	UK	US	G7
CLMX σ^2_{firm}								
lower	-0.134	**0.086**	-0.107	-0.016	-0.375	-0.090	-1.523	-1.020
mean	0.168	0.135	0.175	0.203	0.096	0.103	0.160	0.121
upper	0.469	0.183	0.457	0.421	0.568	0.295	1.843	1.262
σ^2_{idio}								
lower	-0.271	-0.049	-0.204	-0.010	-0.430	-0.135	-1.113	-0.755
mean	0.138	0.067	0.141	0.235	0.076	0.094	0.129	0.102
upper	0.547	0.184	0.486	0.480	0.582	0.324	1.371	0.959

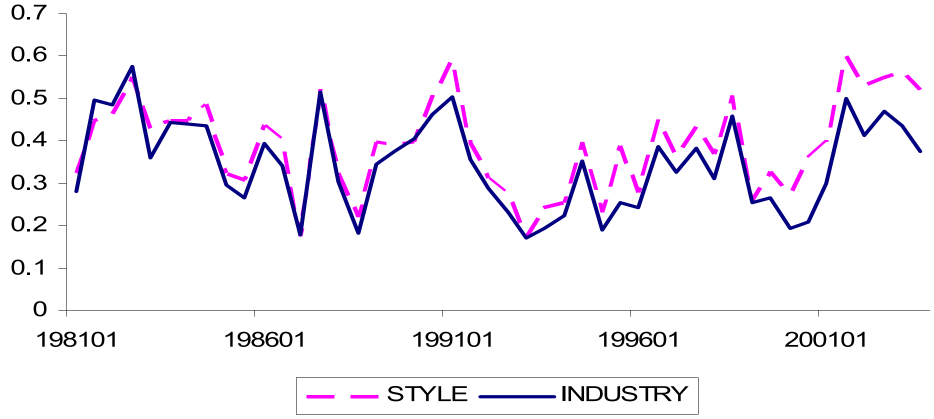
Panel B: Idiosyncratic variance using US only daily returns

	CLMX σ^2_{firm}			
	1964-1997	1964-2003	1981-1997	1981-2003
lower	**0.006**	-0.002	-0.003	-0.032
mean	0.011	0.017	0.006	0.036
upper	0.016	0.036	0.016	0.103
	σ^2_{idio}			
	1964-1997	1964-2003	1981-1997	1981-2003
lower	**0.003**	-0.006	-0.005	-0.042
mean	0.008	0.014	0.005	0.031
upper	0.013	0.033	0.014	0.104

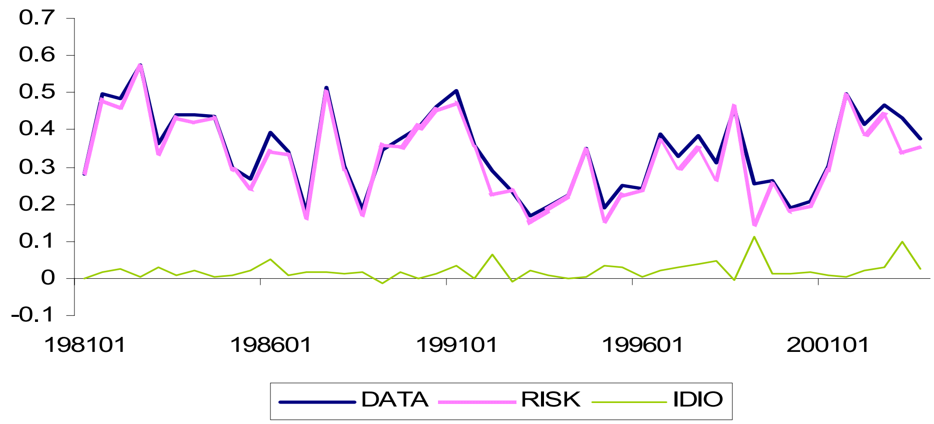
Figure 1. Time-series of portfolio level correlation measure

The sample period is January 1980 to December 2003. Data correlation and its decomposition are defined in equation (16), where DATA refers to γ_{sample}^{CORR}, RISK refers to γ_{risk}^{CORR}, and IDIO refers to the difference between the two or γ_{idio}^{CORR}.

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

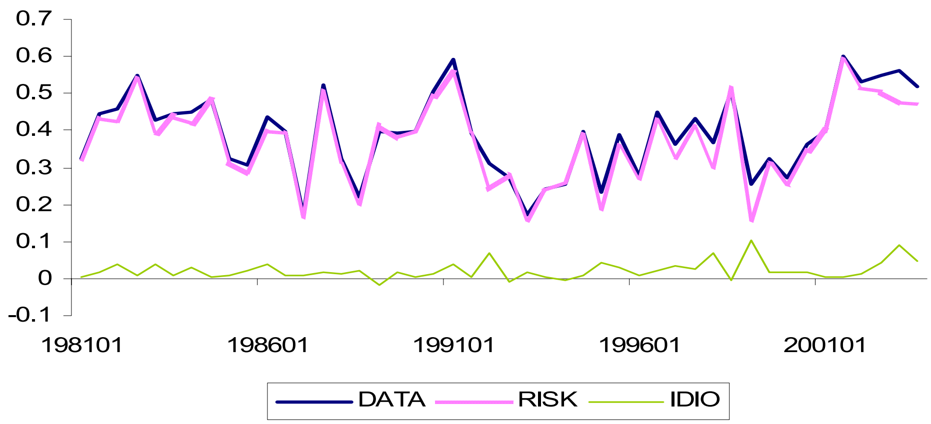
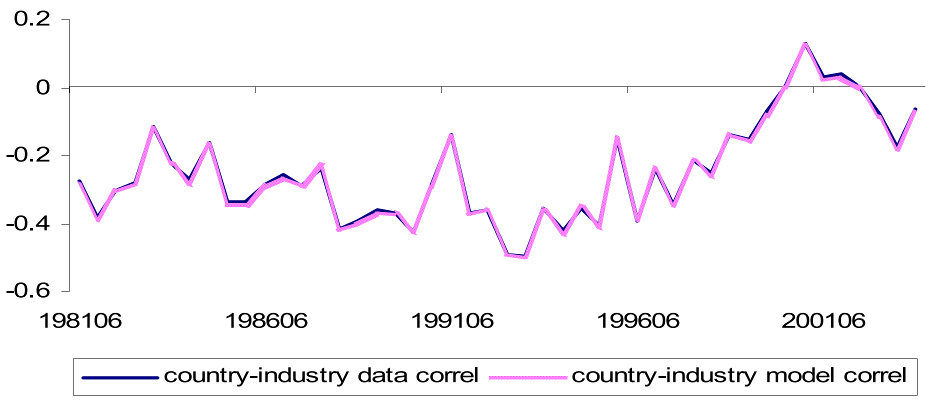


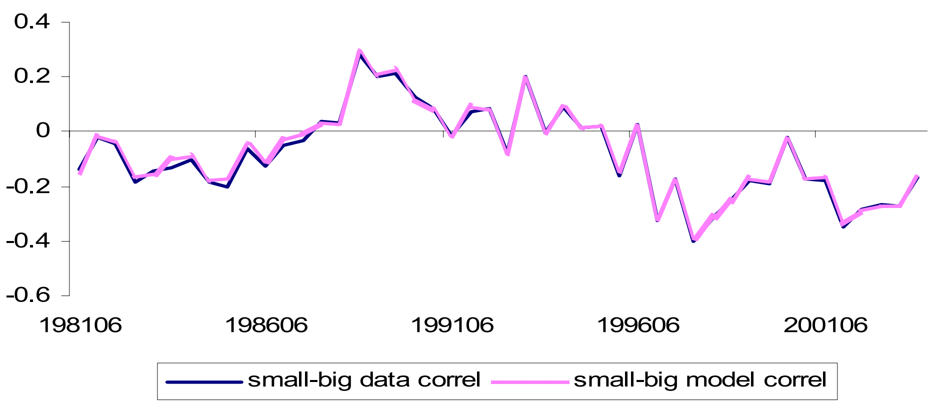
Figure 2. Time-series of portfolio correlation differences

The sample period is January 1980 to December 2003. Data correlation and its decomposition are defined in equation (16), where data refers to γ_{sample}^{CORR}, and risk refers to γ_{risk}^{CORR}. The figure graphs the difference between γ_{sample}^{CORR} (or γ_{risk}^{CORR}) computed using different portfolios.

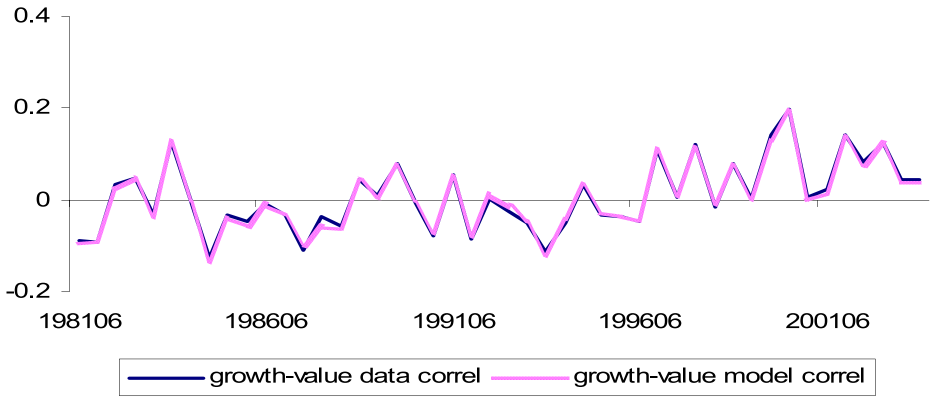
Panel A. Country portfolios minus industry portfolios



Panel B. Style small portfolios minus style big portfolios



Panel C. Style growth portfolios minus style value portfolios



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

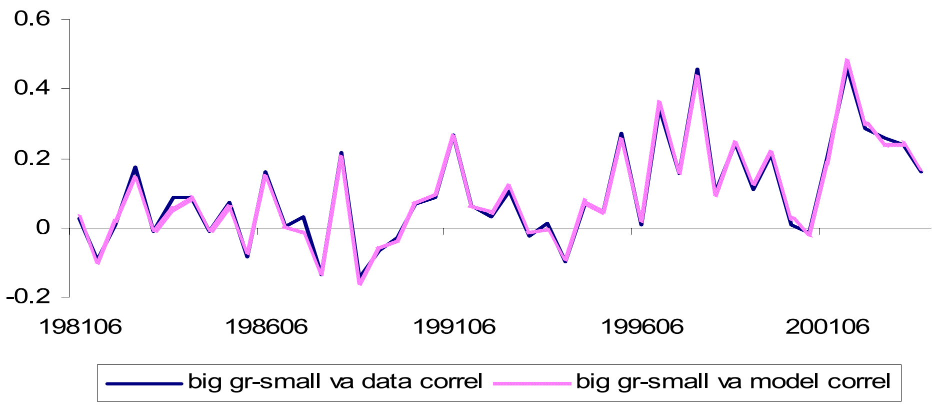
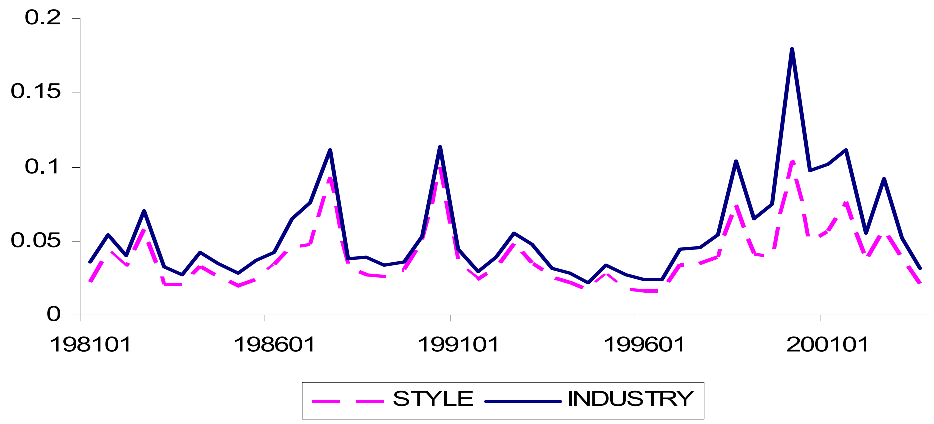


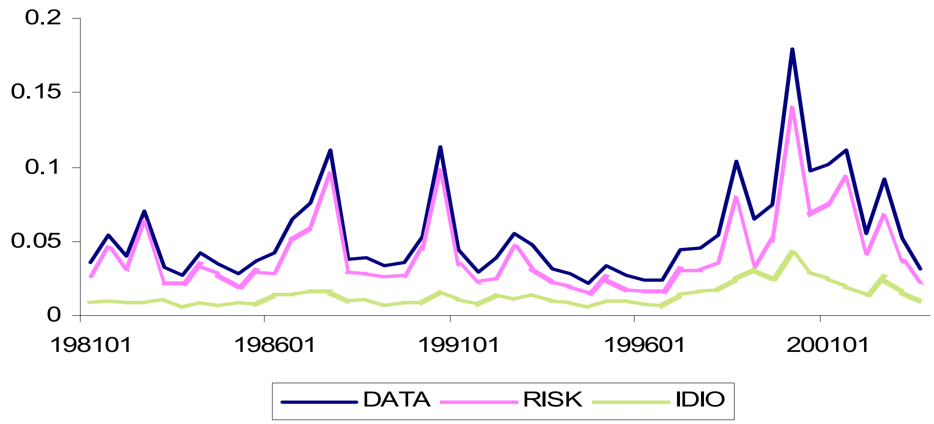
Figure 3. Time-series of portfolio level variance measure

The sample period is January 1980 to December 2003. Data correlation and its decomposition are defined in equation (18), where DATA refers to σ^2_{sample}, RISK refers to σ^2_{risk}, and IDIO refers to the difference between the two or σ^2_{idio}.

Panel A. Data variance measures for country-industry portfolios and country-style portfolios



Panel B. Decomposition for country industry portfolios



Panel C. Decomposition for country style portfolios