The Dynamics of Geographic versus Sectoral Diversification: Is There a Link to the Real Economy?

Francesca Carrieri, Vihang Errunza and Sergei Sarkissian*

McGill University

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* All authors are from the Faculty of Management, McGill University, Montreal, Quebec, H3A 1G5, Canada. Carrieri may be reached at francesca.carrieri@mcgill.ca, Errunza at vihang.errunza@mcgill.ca, and Sarkissian at sergei.sarkissian@mcgill.ca. We thank for helpful comments Lieven Baele, Geert Bekaert, Bruno Gerard, Valter Lazzari, Roberto Rigobon, Pierre Ruiz, and participants of workshops at Arizona State University, Copenhagen Business School, Hong Kong University of Science and Technology, McGill University, Norwegian School of Management BI, University of Wisconsin at Milwaukee, Wilfrid Laurier University, as well as the BSI Gamma Conference on Emerging Markets and the Global Economy, the 2005 American Finance Association Meeting, the 11th Georgia Tech Conference on International Finance and the 2005 International Conference on Business and Finance in Hyderabad. We are also thankful to Ravi Jagannathan and Rene' Stulz for useful discussions on the topic. Jean-Martin Payeur has provided valuable research assistance. The authors are grateful for financial support from IFM2, SSHRC, and BSI GAMMA Foundation. Errunza also acknowledges financial support from the Bank of Montreal Chair at McGill University.

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ABSTRACT

We study the dynamics of gains from sectoral versus geographic diversification and relate economic sources to changes in those gains. We estimate conditional correlations between returns on the U.S. equity market and 16 equity markets and 10 local industries from other OECD countries and find that the average correlation across countries has increased in relation to that across industries. We also show that this process is accompanied by increased alignment in the industrial structures across countries and an increase in the average conditional correlation of aggregate production growth across countries relative to that of disaggregated production growth, especially among developed economies. Thus, the increased benefits of industry-level investing across developed markets are reflected in the real side of the global economy. However, country-level investing should remain the predominant asset allocation approach in emerging markets.

JEL classification: G12; G15

Keywords: Diversification gains; Asset allocation; International equity markets; Industrial structure; Industrial production

1. Introduction

Numerous papers have addressed the question of relative importance of cross-country versus cross-industry diversification. For example, Roll (1992) and Arshanapalli, Doukas, and Lang (1997) suggest that industrial composition can explain substantial variation in national stock returns. However, Heston and Rouwenhorst (1994), Rouwenhorst (1999) find that industrial structure accounts for a very small proportion of variation in national stock market returns. Griffin and Karolyi (1998) and Griffin and Stulz (2001) observe that industries which produce tradable goods have a greater exposure to industry-specific risks but their economic impact on equity returns is still negligible, thus confirming the view of the dominance of country effects.[1] What all these papers have in common is that they do not relate the magnitude or statistical significance of their findings to economic fundamentals. Hence, the purpose of this study is to examine whether the gains from sectoral diversification vis-à-vis country diversification have changed over time, and whether there are identifiable economic forces driving (or related to) these processes.

Erb, Harvey and Viskanta (1994), Karolyi and Stulz (1996), Longin and Solnik (2001), and Ang and Bekaert (2002) find that the correlation structure of international equity returns at the country-level is time-varying. There is also some indication of increasing cross-market correlations among developed markets (see Longin and Solnik, 1995). We thus analyze potential gains from cross-country versus cross-industry investments in a conditional setting to account for changing economic and financial conditions.

Previous studies have identified industrial production growth as one of the important macroeconomic variable linked to equity returns. For instance, industrial production growth is one of the five risk factors in the arbitrage pricing theory model of Chen, Roll, and Ross

[1] Due to the importance of cross-country and cross-industry diversification benefits for portfolio managers, this issue has been widely studied in practitioner publications as well. For the earlier work, see Lessard (1976), Errunza and Padmanablan (1988), Grinold, Rudd and Stefek (1989), Drummen and Zimmermann (1992), and Heston and Rouwenhorst (1995). More recent studies include Baca, Garbe, and Weiss (2000), and Cavaglia, Brightman, and Aked (2000).

(1986). Fama (1981, 1990) finds that stock returns are highly correlated with future industrial production growth. Moreover, Dumas, Harvey, and Ruiz (2003) provide a theoretical framework where cross-country equity market correlations are modeled as a function of output correlations. More recently, Hong, Torous, and Valkanov (2006), using both U.S. and international data, show that returns on some industries are closely related to industrial production growth. Hence, we conjecture that there might be a link between the dynamics of correlations for country and industry-level market returns with the dynamics of correlations for country and industry-level production growth.

We use a sample of monthly equity market returns over 1976-2003 from 17 OECD countries and 10 local industries which practically span the entire market in each of these countries, as well as a sample of monthly aggregate and disaggregated industrial production growth rates across all countries over 1986-2003. We estimate the average pairwise conditional correlations between stock market returns for the U.S. and the other OECD countries as well as their corresponding local industries from a bivariate GARCH(1,1) model. We find that the average correlation across countries has increased in relation to that across industries and that this increase has been gradual since the late 1980's.

While the on-going financial and economic convergence around the world is thought to be responsible for the increase in international market correlations, we show that it is also accompanied by the increasing alignment in the industrial mix between the U.S. and other markets starting from the beginning of the 1990's. During 1990-2003, the proportion of a given industry's representation in a country's market capitalization has become more similar to that in the U.S. and this difference is statistically significant. This is especially true for the largest developed economies. We also observe a positive and significant relation between changes in the alignment in the industrial mix among developed countries and changes in their equity market correlation with the U.S.

We link this phenomenon to changing economic conditions. Similar to equity returns, we estimate the average pairwise conditional correlations between industrial production growth rates for the U.S. and the other OECD countries as well as their corresponding disaggregated series. We show that the increased importance of sectoral diversification vis-à-vis geographical diversification is mirrored in the increase in the average correlation of aggregate production growth across countries relative to that of their disaggregated production growth, especially among developed economies. Thus, the increasing benefits of industry-level investing across developed markets are reflected in the real side of the global economy. On the other hand, country-level investing should remain the predominant asset allocation approach in emerging markets.

The rest of the paper is organized as follows. Section 2 describes the two datasets and reports summary statistics. Section 3 introduces our conditional methodology and provides the estimation results for stock markets and production growth rates. Section 4 investigates the plausible reasons for the changes in the gains from cross-country versus sectoral diversification. In this section, we also report tests on the industrial structure alignment and establish a link between the dynamics of equity returns and industrial production growth rates at the aggregate and disaggregated level. Section 5 concludes.

2. Data

We work with two distinct datasets. The first one contains aggregate and disaggregated equity returns while the second one contains aggregate and disaggregated industrial production growth rates. Industrial production is particularly useful for the purpose of our paper since, unlike other macroeconomic variables such as inflation, interest rates etc. it is observable not only at the aggregate but also disaggregated level.

2.1. Equity returns data

We use monthly returns from Datastream over the period January 1976 to December 2003, for 17 OECD countries: Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Korea, Mexico, Portugal, Spain, Sweden, the U.K., and the U.S.[2] Our set of local industries consists of 10 broad industry categories, which correspond to the Level 3 classification in Datastream, namely: basic industries, cyclical goods, cyclical services, financials, general industries, information technology, non-cyclical goods, non-cyclical services, resources, and utilities. This guarantees that the set of our local industries practically spans the entire equity market in each country. All country and local industry returns are converted into U.S. dollars using the corresponding exchange rates.

Our sample does not cover a larger set of countries because local industry indexes and disaggregated economic variables, which we use later in the paper, are not available for a number of countries, including developed ones.[3] Also, not all countries and industries have data during the entire sample period. For instance, the total number of local industries across all the countries excluding the U.S. is 132, and the corresponding number of industries with their return series available during our entire sample period is 66.[4]

Plot A of Figure 1 presents the frequency of equity return data at the country and industry levels over time. One can notice that the most significant increase of the cross-section of our asset returns occurs in the beginning of the 1990's. This is when the data series for several emerging and small developing countries become available at both the aggregate and disaggregated levels. This is the main motivation to focus on the post 1990 sample in many of our tests.

[2] The Datastream Global Equity indices represent approximately 75%-80% of the total market capitalization in the respective countries and local industries. Note that since Datastream backfilled the data until 1999 our entire sample has some survivorship bias. However, since we perform many of our tests on the post-1990 sample only, it significantly reduces any potential effect of the survivorship bias on our results and conclusions.

[3] We are unable to use finer industrial classifications like, for example, Griffin and Karolyi (1998), since industrial growth rates at the corresponding aggregation level are not available for most countries.

[4] We excluded two local industry returns, namely, non-cyclical services from Austria and cyclical goods from Portugal because of breaks in their return index series.

Table 1 provides summary statistics for equity returns, including the mean, standard deviation, the Ljung-Box tests for autocorrelation of order twelve for raw returns and squared returns, the Bera and Jarque (1982) test for normality, and the average cross-correlation. Panel A reports these estimates for country-level returns. Mexico has the highest mean monthly return of 1.54%, followed by Ireland (1.44%) and Sweden (1.44%). The lowest return is for Portugal – 0.65% per month. Korea has the highest volatility, which is expected since our sample period includes the East Asian crisis. The U.S. market has the lowest volatility. There is no overwhelming evidence of significant autocorrelation across countries: only four equity market returns have monthly autocorrelation significant at the 5% level. However, the autocorrelation of squared returns is significant across eight markets. This observation, along with the results of the Bera-Jarque test, which is very significant for most of the returns, highlights the importance of accounting for the deviations from normality in the estimation of our model. The average cross-country equity market correlations range from 0.22 for Korea to 0.52 for France. The last column of the panel shows the number of different industries per country. Only five countries in the sample have all the ten industries. Greece, on the other hand, has four industry series available.

Panel B of Table 1 shows the summary statistics for disaggregated (local) industry returns. For the ease of exposition we created equally weighted averages of the returns for each broad industry group excluding the U.S. – an equivalent of the equally weighted global industry group. The overall results are similar to country-level statistics, i.e., we can observe some autocorrelation of squared returns and significant deviation from normality. Across the ten sectors, information technology and non-cyclical services, which include telecommunication, command the largest mean monthly returns, 1.73% and 1.67%, respectively. Information technology sector also has the largest volatility. The worst performing sector during our sample period is cyclical goods. The average cross-industry correlations range from 0.57 for information technology to about 0.79 for cyclical services and general industries. The last column of the panel shows the number of countries contributing to a given global industry. Not surprisingly, only eight countries have a meaningful data series on information technology. The sectors with the broadest cross-country representation are basic industries, financials, and non-cyclical goods.

2.2. Industrial production data

We collect industrial production growth rates for all the countries in our sample over the 1986-2003 period from Datastream. These data are monthly and seasonally adjusted.[5] We consider both aggregate industrial production growth rates for each country as well as disaggregated industrial production growth rates for the following 10 industries: basic metals, chemicals, electrical equipment, food, machinery, mining, pulp & paper, textiles, transport equipment and utilities. These categories span our set of broad equity industries to the largest extent possible given data limitations.[6] However, as with local industry equity data, not all industrial production categories are available in each country and/or during the entire sample period.

Plot B of Figure 1 shows the frequency of industrial production data at the country and industry levels over time. Similar to equity returns, the largest increase of the cross-section of these data occurs in the beginning of the 1990. By that time both country and industry-level industrial production data become available for most of the countries and industries. This observation coupled with the similar one for equity returns encourages us to compare the dynamics between the two series primarily in the post-1990 period.

Table 2 provides the properties of industrial production growth rates across countries and industries. It reports the same statistics as Table 1. Panel A reports estimates for aggregate industrial production growth. Ireland has the highest mean growth rate of more than 1% per month followed by Korea with about 0.7% growth. The volatility is also the highest for Ireland. Notice that unlike equity returns, production growth shows much more evidence of significant autocorrelation. It is significant across all countries except Korea, while the

[5] Datastream reports each observation for industrial production in the middle of the month.
[6] We do not account for construction output because aggregate industrial production data excludes this sector.

autocorrelation of squared growth rates and the Bera-Jarque test are significant across most of the countries. The panel again highlights the importance of accounting for the deviations from normality in the estimation of conditional correlations. The average cross-country correlations in industrial production growth range from negative 0.02 for Sweden to 0.12 for Italy. These numbers are substantially lower than the corresponding cross-market correlations in Table 1. The last column of the panel shows the number of disaggregated industrial production series per country. Only two countries in the sample (Japan and Korea) have all the ten industry level series. Mexico however is left with only two industry-level industrial production data.

Panel B of Table 2 shows the summary statistics for the disaggregated industrial production growth rates. Also in this case, for the ease of exposition, we present equally weighted averages of the growth rates for each broad industry group. The overall results are similar to country-level statistics, i.e., we observe more significance of autocorrelation in disaggregated production growth rates than among industry-level equity returns. Across ten industry-level production growth series, textiles have the lowest mean monthly growth of negative 0.05% per month, while electrical equipment – the largest, 0.57% per month. The last column of the panel shows the number of countries contributing to a given disaggregated production sector. Only three countries have data on mining industry.

3. Methodology and results

To examine the dynamics of changes in diversification potential across countries versus industries over time in more detail, we use a conditional framework where means, variances and covariances are assumed to be time-varying. The conditional setting allows us to obtain correlation estimates making the full use of our data sample, which is somewhat limited for some equity data along the time dimension. Moreover, a similar procedure is also applied to the economic series, for which the data availability issue is even more critical. The application of the same methodology to two different sets of data allows us to directly compare our results across both estimations.[7]

3.1. Estimation of conditional correlation

In analyzing the potential diversification benefits with the equity data, we take the position of a U.S.-based investor who is fully diversified in the domestic market and therefore consider the U.S. market portfolio as our base asset. We then compare the estimated correlations between the base asset and other country indexes with that between the base asset and industry indexes. Following Harvey (1991), Ferson and Harvey (1993), Dumas and Solnik (1995) and others, we account for the changing global economic conditions through the use of information variables in the return generation process.

Specifically, we model an asset return at time t as a linear function of variables that are observable to investor at time t-1 as,

$$r_{i,t} = E\left[r_{i,t} \mid \mathbf{Z}_{t-1}\right] + e_{i,t} = \mu_i + \mathbf{b}_i \mathbf{Z}_{t-1} + e_{i,t}\,, \tag{1}$$

where $r_{i,t}$ is the equity return on the i-th country or industry index, μ_i is the unconditional mean return of asset i, $\mathbf{Z}_{t-1}$ is the vector of lagged information variables that conveys information about global economic conditions, $\mathbf{b}_i$ is a set of coefficients, and e_i is the disturbance term. Given the recent evidence on stock returns predictability (e.g., Avramov, 2002; Ang and Bekaert, 2003; Ferson, Sarkissian, and Simin, 2003), our information set includes the lagged U.S. term spread and the lagged credit spread as the difference between the three-month Eurodollar rate and the three-month U.S. Treasury-bill rate.

To investigate the dynamics on the real economy side, we adapt the statistical process based on the properties of the industrial production time series. Due to the strong evidence of

[7] On the other hand, a methodology similar to Heston and Rouwenhorst (1994) would be directly applicable only to equity returns.

significant autocorrelation in industrial production growth rates, we model the growth process at time *t* as a linear function of its two lagged observations, i.e., as an AR(2) process:

$$IP_{i,t} = \psi_i + b_{1i} IP_{i,t-1} + b_{2i} IP_{i,t-2} + e_{i,t}, \tag{2}$$

where $IP_{i,t}$ is the aggregate or disaggregated industrial production growth at time *t*, ψ_i is the unconditional average production growth, and e_i is a disturbance term.

We use equation (1) or equation (2) to estimate a series of bivariate systems, where the first equation describes the dynamics of the foreign time series (returns or industrial production), while the second equation corresponds to the U.S. time series (the U.S. equity market portfolio or the US industrial production growth rate).[8] In both of these systems,

$$e_t' = \left[e_{i,t}, e_{b,t} \right] \sim N(0, H_t), \tag{3}$$

where H_t is the conditional variance-covariance matrix, and e_b is the return innovation on the U.S. time series relative to which the correlations are computed.

For the equity series, given the evidence of non-normality in returns (see Table 1), we follow Glosten, Jaganathan, and Runkle (1993) and Kroner and Ng (1998) and specify the conditional variance-covariance matrix as an asymmetric GARCH(1,1) process but augment it with a time trend, namely,

$$H_t = C'C + A' e_{t-1} e'_{t-1} A + B' H_{t-1} B + G' \eta_{t-1} \eta'_{t-1} G + D * T, \tag{4}$$

where *C* is a (2x2) upper triangular matrix, *A*, *B* and *G* are the (2x2) diagonal matrices, η_{t-1} is a vector of negative shocks with $\eta_{t-1} = e_{t-1}$ if e_{t-1} is negative, and 0 otherwise, D is a (2x2) matrix with zeros and ones as diagonal and off-diagonal elements respectively, T is a (2x1) vector with t as its characteristic element and "*" is the Hadamard matrix product. For the industrial production series, we use the same specification for the second moments but do not include the asymmetry component.

[8] Bivariate GARCH (1,1) models have been used in international asset pricing literature before. For instance, Chan, Karolyi, and Stulz (1992) measure the influence of foreign assets on the U.S. market portfolio, while Longin and Solnik (1995) examine the stability of national equity market correlations.

Aside from the asymmetry, our specification for the H matrix is the traditional BEKK diagonal specification of Engel and Kroner (1995) with the addition of a linear time trend in the conditional covariance.[9] We modify the covariance parameterization to test for a structural change in the correlation structure of the series. While there is substantial evidence that the conditional correlations have increased among the aggregate indices of the large developed countries, there is no similar evidence on the dynamics of correlations at the industry level. Our approach is similar to the correlation tests of Longin and Solnik (1995) where the constant conditional correlation model is modified with the introduction of a time trend. An alternative approach would be to follow Bekaert and Harvey (1997) and make variance-covariance matrix of equity returns a direct function of information variables. However, there is no indication as to the predictive variables that would be common to both the equity returns and economic series. Therefore, for the consistency of our methodology and results across the estimation of the two datasets, we use a purely statistical model for our inferences.[10]

We estimate parameters of the model by the quasi-maximum likelihood method (QML) of Bollerslev and Wooldridge (1992). The QML estimator is consistent and distributed normally asymptotically allowing us to conduct regular statistical inference. As with the standard maximum likelihood estimation, QML estimates are obtained by maximizing the log likelihood function over the parameter space Θ, i.e.,

$$\underset{\Theta}{\mathrm{Max}} \sum_{t=1}^{T} \ell_t(\Theta),$$

where T is the number of observations and

$$\ell_t(\Theta) = -\frac{TN}{2}\ln 2\pi - \frac{1}{2}\sum_{t=1}^{T}\ln\left|H_t(\Theta)\right| - \frac{1}{2}\sum_{t=1}^{T}\varepsilon_t(\Theta)' H_t(\Theta)^{-1}\varepsilon_t(\Theta). \quad (5)$$

[9] We do not add a time trend in the conditional variance because the estimated correlations are essentially unaffected by this omission. However, the inclusion of variance trend makes the convergence of estimation more difficult for some series, and so we focus here on a more parsimonious specification.

[10] Bekaert and Harvey (1997) model conditional variance of returns as a function of two information variables: the market capitalization to GDP ratio and the size of the exports plus imports to GDP ratio. Note that both of these variables are upward trending.

To obtain the parameter vector Θ, we use the BFGS optimization algorithm (see Shanno, 1985).

To summarize the time series of each of the bivariate correlations, we compute the average of conditional pairwise correlations (APCC), defined as:

$$\overline{\rho}_{bi,t} = \frac{1}{n}\sum_{i=1}^{n}\frac{\mathrm{Cov}_t\left(r_{b,t+1}, r_{i,t+1}\right)}{\sigma_{b,t}\sigma_{i,t}}, \qquad (6)$$

where r_b and r_i correspond to the returns on the base (US) time series relative to which the correlations are computed and the foreign (non-US) asset, respectively, while σ_b and σ_i are their respective conditional standard deviations.[11] We compute the average of the conditional correlations for industrial production growth in the same way.

3.2. Test results for equity returns

We first present the residual diagnostics summary from the estimation of equity market correlations.[12] Table 3 shows no evidence of asymmetry or autocorrelation in the residuals or squared residuals. There is still evidence of non-normality of the residuals but it is significantly weaker for many countries compared to that in raw returns in Table 1. For example, across industries, only two residual series, for cyclical goods and financials, show significant non-normality at the 5% level, yet seven global industries in Table 1 are not normal at the same significance level.[13]

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[11] Alternatively, one could compute the correlation between returns on the base asset and the portfolio of all other assets as in, for example, De Santis and Gerard (1997). Our measure is more precise and produces a wider set of possible values, i.e, the point estimate of ρ has a smaller variance and our measure is more informative. A proof and Monte-Carlo simulation results are available from the authors on request.

[12] We do not impose a constraint on the correlation bounds in the estimation since all our correlation estimates always stay between -1 and +1.

[13] The sample of correlations includes 130 series instead of 132. The model generates few series with a very persistent variance. For seven series, this feature was corrected through the estimation of a more parsimonious GARCH model without asymmetry. However, two series showed persistent variance even based on the parsimonious model, and so they were excluded to preclude any biases in the estimated correlations. On the other hand, we leave in the correlation sample two series with evidence of nonstationarity in their GARCH parameters. Since these series start in the 1990's, the nonstationarity could be due to the short observation period.

Figure 2 shows the time dynamics of the average pairwise conditional correlations. Plot A depicts correlations between the U.S. equity market returns and returns on the indexes of the other 16 OECD countries (country level correlation), and the indexes of local industries excluding the U.S. (industry level correlation). The plot shows that both country- and industry-level correlations have markedly increased and this increase has accelerated in the beginning of 1990's. However, while in the 1970's and 1980's the difference between the average correlations at the country and industry levels was relatively small, by the early 2000's the spread has increased markedly to almost 0.20. Plot B illustrates the dynamics of the correlation spread in equity returns over the entire sample period. The changes in this spread over time and especially in the 1990's suggest that in relative terms industry diversification has gained more importance vis-à-vis country diversification.

To attest to the statistical significance of our findings, Table 4 presents the test results on correlation trends in equity returns based on model (1) and (4). The table shows the average point estimates of the trend coefficients in cross-correlations of the U.S. equity market index returns with country- and industry-level equity returns for the remaining 16 OECD countries. It reports the average trend, the number and average value of negative and positive trend coefficients, as well as the number of negative and positive significant trend coefficients. We show results for the entire cross-section of data and separately for three country groups: large developed markets, small developed markets, and emerging markets. At the country level, all trend coefficients are positive and on average marginally significant for smaller developed and emerging markets. The overall results are still somewhat close to marginal significance. At the industry level however, the proportion of (marginally) significant trend coefficients is substantially lower. Moreover, there are non-trivial instances of negative trends, including one negative and significant for a local industry in the set of small developed countries.

These results may look somewhat similar to those in Baca, Garbe and Weiss (2000) and Cavaglia, Brightman, and Aked (2000), yet there is a fundamental difference. In both of these papers, the increase in the importance of industry factors is limited to a two-year period from

1997 to 1999. In a similar vein, Brooks and Del Negro (2003) suggest that the relative importance of industry factors is directly linked to the Internet bubble and so it is a short-lived and transitory phenomenon. As Figure 2 illustrates, our conditional estimates show a steady increase in the correlation spread almost over the entire sample period. This implies that the increase in the importance of industry factors for diversification purposes has been gradual and not limited only to the late 1990's. The distinction is important since it suggests that the greater benefits of sectoral diversification vis-à-vis geographic diversification are not likely to be related to the peculiarity of the world equity markets in the late 1990's. We discuss this issue in more detail in the next section.

Our results are consistent with Campbell et al. (2001) who document an increase in the U.S. idiosyncratic volatility versus market-wide volatility and Ferreira and Gama (2005) who find larger local industry volatility relative to market and country in a global setting for the more recent period. If the volatility at the firm or industry level is increasing relative to that at the market level, then correlations at the market level are also likely to increase relative to those at the industry level. We show the dynamics of average conditional volatility across all country (excluding the U.S.) and industry returns in Figure 3. There are no visible trends in the volatility dynamics. There are, however, instances of high volatility clusters in certain time periods, such as in the late 1980's to early 1990's, and in the late 1990's.[14] A careful look at the correlation spread in Figure 2 gives some indication that periods of higher volatility may coincide with bigger increases in the spread between country-level and industry-level correlations.[15] Finally, we can also observe that the difference between the two volatility series is smaller in the beginning of the sample period than at the end, corroborating the findings in Campbell et al. (2001), and Ferreira and Gama (2005).

[14] Much of the volatility increase in the late 1980's and early 1990's can be attributed to the beginning of liberalization changes in many developed and emerging markets. Baele (2005) finds, for instance, that this period coincides with an increase in the shock spillover intensity among European countries.
[15] Catao and Timmermann (2003) show that industry factors become more important in high global volatility states.

3.3 Test results for the real economy

The diagnostics from the estimations of equation (5) for the conditional correlations of industrial production growth rates are in Table 5. The residuals show no signs of asymmetry or autocorrelation in the vast majority of the squared series. There is still evidence of autocorrelation but it is generally much weaker across countries and industries than for the corresponding raw data in Table 2. While many residual series are not normal, especially at the country level, the extent of this non-normality is not as overwhelming as in the original production growth data.[16]

Figure 4 shows the time dynamics of the average pairwise conditional correlations of industrial production growth. Plot A shows that the average country-level correlation is higher in the later half of the sample period than in the beginning. However, at the disaggregated industry level, the average conditional correlation did not increase at all, and, if anything, it seems somewhat lower in the late 1990's than in the early 1990's. As a result, while in 1986 the difference between the average correlations at the country and industry levels for production growth rates was negligible, by the early 2000's the spread had increased to more than 0.1. Plot B shows the dynamics of the correlation spread in industrial production over the entire sample period. The overall changes in this spread are remarkably similar to those for equity returns. Therefore, it appears that the increasing importance of industry diversification vis-à-vis country diversification in recent years has its reflection in the changes of the countries' real output.

To analyze the statistical significance of our findings, Table 6 reports the results of the tests on correlation trends in industrial production growth. The table shows the average point estimates of the trend coefficients in cross-correlations of the U.S. industrial production growth

[16] The sample of correlations includes 128 series instead of 133. As with equity returns, for a few series the model generates a very persistent variance. For 15 series, this feature was corrected through the estimation of a more parsimonious model with an AR(1) or a constant for the mean. However, five series showed persistent variance even based on the parsimonious model, and so they were excluded to preclude any biases in the estimated correlations. Also in this case, we leave in the sample five correlation series with evidence of nonstationarity in their GARCH parameters. Since these series start in the 1990's, the nonstationarity could be due to the short observation period.

with country- and industry-level production growth rates for the remaining 16 countries. Unlike trend estimates for equity return correlations, the vast majority of which were positive, production growth correlations have a substantial number of negative trends. Yet, similar to equity return correlations, in relative terms, there is more statistical evidence for upward trends at the country level than industry level. At the country level, across all countries, there are five negative but insignificant trend coefficients, while the number of positive trend coefficients is 11, out of which 3 are significant. At the industry level, across all countries, the picture is different: there are 62 negative trend coefficients, out of which 9 are significant, while the number of positive trend coefficients is 65, out of which only 6 are significant. In addition, we can see that the highest ratio of the number of significant negative to significant positive trend coefficients is observed for the largest developed markets (6 to 3), followed by the smaller developed markets (3 to 2). In emerging markets, there are no significant negative trends. Thus, these findings confirm that the divergence of average country- and industry-level correlations of industrial production growth rates (increase in the industrial production correlation spread) reported in Figure 4 has a substantial statistical backing.

4. Why have the relative industry diversification gains increased?

The similarity between the results of the tests on equity returns and industrial production growth suggest that there are "real economy" forces that may explain the increased importance of sectoral diversification in recent years.

A number of authors have suggested that the economies of the developed and, to a certain extent, developing world are becoming more closely aligned. For example, De Santis and Gerard (1997) find that the G-7 counties are effectively integrated with the world market. Dumas, Harvey and Ruiz (2003) find that the correlation among the OECD equity markets is consistent with the integration hypothesis. Hardouvelis, Malliaropulos, and Priestley (2006) link the increase in average correlations among the European markets with the ongoing economic integration processes in Europe. Bekaert and Harvey (1995) and Carrieri, Errunza and Hogan (2005) show that integration processes are increasing overtime not only in developed but also emerging markets. There has also been an increasing financial convergence among many countries, most notably the money markets and foreign exchange markets of the European Union in the 1990's. Taken together with the evidence on increasing economic integration, this suggests that the potential benefits of geographic diversification across these countries over the same time period should have been declining.

Thus in this section, we explore what could potentially contribute to the documented patterns of equity market correlations. First, we examine if there are changes in the industrial composition of national equity indices that can explain cross-correlation patterns in equity returns. This approach is in the spirit of Roll (1992) who argued that the cross-country pattern of correlations is due to the industrial composition of countries. We then provide a link between industrial production growth rates within each country and the widening spread between the average correlations of country and industry returns.

4.1. Industrial structure alignment

Roll (1992) notes that in part the returns on equity markets could be driven by differences in the industrial composition of different country returns. Further, Dumas, Harvey and Ruiz (2003) model cross-country equity market correlations as a function of output correlations.

We first investigate country level alignment by looking at the average changes in the industrial composition of all countries relative to that of the U.S. over the entire sample period. Note that as with our correlation analysis, we take the U.S. investor perspective. For each month, the alignment is computed from the average absolute difference between each local industry proportion in the U.S. total equity market capitalization on one side and each of the remaining 16 countries on the other. Figure 5 plots the time-series of our measure of alignment and shows the dynamics of the average alignment across all countries and industries, of all the series excluding information technology sector, as well as those series that existed during the entire sample period (66 in total). Starting at the beginning of 1990's, there is a sizable increase in the alignment (decrease in misalignment) of industrial structure of the U.S. and other markets. Interestingly, when the information technology is excluded, the alignment is even stronger. Since many return series in our sample start at around 1990, their mere addition to the sample could have had a mechanical implication on the alignment dynamics. The plot of the alignment structure based only on those series that existed during the entire sample period confirms our previous result. It is worth pointing out that this smaller sample contains industry returns primarily from the largest developed countries.

We next examine the extent of the industrial structure alignment across countries and industries in more detail, especially after 1990, when most of the changes have occurred. Table 7 presents the results. Panel A shows the average absolute differences between the proportions of market capitalization of a given industry in the U.S. market and that in the equity market of each country. The last column reports the change (spread) in these differences from the first period to the second with the corresponding t-statistic. We find that the absolute difference between each sector's representation in the U.S. and other countries' markets is larger in the first sub-period than in the second, 9.50% and 8.49%, respectively. Across all countries, the industrial structure alignment is present in 11 out of 16 countries. Among the three country groups, the largest change is observed among emerging markets (2.19%), followed by large developed countries (0.95%).[17]

Panel B of Table 7 investigates industrial alignment by taking the global sectoral diversification perspective. We report the proportion of market capitalization of each industry in the U.S. total equity market and the equally weighted average of similar proportions for the same industry across all other countries in the sample over the two calendar periods, as well as the absolute differences in these measures. In the U.S., the largest gains in the market cap from

[17] Emerging markets have reached in relative terms a larger alignment of their industrial structures towards that of the U.S. in the 1990's than other countries in the sample. However, the level of their difference with the U.S. is still markedly higher than for the largest developed countries.

the first sub-period to the second are for information technology and financials, from 9.11% to 18.71% and 12.57% to 18.82%, respectively. In other countries of the sample, the largest increase in the relative market caps is for non-cyclical services, from 8.91% to 15.50%, while the largest decrease is for basic industries, from 15.48% to 9.67%. The last two columns of the panel show that the alignment of industrial structures across sectors is not overwhelming: the average industry-level alignment over the 1990-2003 period is only –0.50% which is insignificant.

Thus, the results in Figure 5 and Table 7 show a general tendency towards convergence in the industrial structures of the U.S. and the rest of the world with more evidence of this alignment at the country level than the industry level. This is one of the potential explanations for the increase in country and industry level correlations with the U.S. market. Figure 6 illustrates the link between changes in correlations of equity returns and industrial structure alignment. We expect that countries that experienced increased industrial alignment should display larger increases in return correlations. Plot A remarkably shows that this is indeed the case for large developed markets and this relation is highly significant in spite of the small sample size. However, we find no clear pattern for small developed or emerging markets in Plot B.

The increased alignment in industrial structure across countries, especially among large developed markets, also points out that there are fundamental causes of this phenomenon since the evolution of market capitalization across industries is likely to reflect their relative importance in the real economy. In the next sub-section, we further explore the link between equity returns and the real economy.

4.2. The link between correlation spreads in equity returns and industrial production growth

Since the change in international diversification benefits depend on the relative changes in correlations, we now focus on the explicit relation between correlation spread in equity returns and industrial production growth for different country sets. We conjecture that the correlation patterns observed with country-level and industry-level equity returns should have some reflection in the correlation patterns between aggregate and disaggregated industrial production growth rates.

Figure 7 depicts the average annualized non-overlapping correlation spread for equity returns and industrial production growth rates for our three country groups.[18] The plots indicate that the spread between country- and industry-level equity return correlations have increased more dramatically for developed markets than emerging. For both large and small developed markets, the spread increased from about 0.05 in 1986 to more than 0.20 by the early 2000's. For emerging markets, over the same time period the spread increased from less than 0.05 to slightly more than 0.10. For industrial production growth rates, the biggest increase is observed for the developed economies. Not only spreads in conditional correlations between aggregate and disaggregate industrial production growth rates follow the corresponding trends in equity return correlation, but also their dynamics very closely resembles that of the equity spread. This remarkable feature of the industrial production spread is applicable to all three plots. For instance, among the largest developed countries the maximum divergence between country- and industry level correlations for both equity returns and production growth rates is recorded in 2001. Thus, the spread in the equity market correlations appears to have an equivalent reflection in the real side of the global economy.

As Figure 7 illustrates, the correlation spreads in equity returns and industrial production growth rates may share a common trend and/or have synchronous changes in their dynamics. To investigate these links in a direct statistical setting, we start with testing for common deterministic trends in the two correlation spreads using the methodology of Vogelsang and Franses (2004). We use the heteroskedasticity and autocorrelation consistent (HAC) estimator $\hat{\Omega}$ with the Bartlett kernel (see Newey and West, 1987), i.e.:

[18] Chen, Roll, and Ross (1986) point out that except for the annual frequency, the industrial production growth data is often quite noisy to be treated as an innovation for equity returns.

$$\hat{\Omega}_{HAC} = \hat{\Gamma}_0 + \sum_{j=1}^{T-1}\left(1 - \frac{j}{S_T}\right)\left(\hat{\Gamma}_j + \hat{\Gamma}_j^{'}\right), \tag{15}$$

where $\hat{\Gamma}_j = T^{-1}\sum_{t=j+1}^{T}\hat{U}_t\hat{U}_{t-j}^{'}$, so that U is the $T \times K$ matrix of residuals from K univariate regressions on the trend variable. We use two variations for the bandwidth S_T, constant and automatic.[19]

Table 8 reports the results of Wald tests on common trends in equity and industrial production correlation spreads for our two bandwidth choices. It also shows the degrees of freedom for each test. Based on the constant bandwidth, we reject the existence of a common trend across all countries at the 5% level and separately for the smaller developed countries and emerging markets groups at the 10% level. The evidence suggests that in the largest developed markets the two correlation spreads share the largest common trend component. In the last two columns we test for a common trend across six series: three equity correlation spreads and three industrial production correlation spreads. The test strongly rejects the null of a common trend among all six series. However, when the emerging market group is excluded (the last column), the test statistic drops substantially and the common trend component is no longer rejected at the 5% level. The replacement of the constant bandwidth with the automatic one qualitatively changes results only for emerging markets. The common trend component for the two spreads in this country group is now rejected at the 1% level. Therefore, we conclude that only developed countries, especially the largest ones, show comparable increase in both equity and industrial production correlation spreads.

Finally, we examine whether the relation between the two spreads goes beyond the common trend component. In doing so, we also account for the impact of other variables related to ongoing economic integration, such as the industrial structure alignment, financial development, proxied by the ratio of country's market capitalization to its GDP, and market openness, proxied by the ratio of the sum of country's exports and imports to its GDP. For the

[19] The constant bandwidth sets $S_T = T$, the sample size. The automatic bandwidth is modeled using an AR(1) process as in Andrews (1991), due to the high first-order autocorrelation of the series.

ease of exposition and interpretation of result, we invert the industrial structure alignment measure to match the upward trend in the correlations series.

Table 9 shows the results. Panel A reports the auto- and cross-correlations. The cross-correlations are all positive and relatively high. Note that except for the correlation spread in industrial production growth, which has the autocorrelation of 0.75, the other three variables are very highly persistent: the autocorrelation exceeds 0.98 and 0.99 for industrial structure alignment and financial development variables, respectively. In part, the observed high auto- and cross-correlations are driven by upward trends in most of these variables. Since it is known that regressing one highly correlated variable on another may lead to spurious results, in our regressions, we detrend all the variables and use the changes in the financial development series rather than its level.[20]

The results of the regression of detrended correlation spread in equity returns on all other detrended variables are reported in Panel B of Table 9.[21] The standard errors in the regression are computed using the HAC variance-covariance matrix with automatic lag selection for the moving average term. Regressions (1-3) show that with detrended series there is no residual relation between correlations spread in equity returns and industrial production growth across all country groups. The adjusted R-squared in all regression are less than 1%. This result should not be surprising given Chen, Roll, and Ross' (1986) remark about the noisiness of industrial production growth data at the monthly frequency. We add the other three regressors in Regressions (4-6). Their inclusion substantially increases the regression fit across all market groups. The R-squared are now between 3% and 9%. The change in the market openness appears to be important for the increase in correlation spread in the largest developed and especially emerging markets, thus supporting Forbes and Chinn (2004) who show that changes in global trade have a substantial impact on cross-market equity correlations. This outcome is quite intuitive since the market openness measures the trade to GDP ratio and

[20] See Granger and Newbold (1974) and Phillips (1986).

[21] For an example of a regression with correlation as a dependent variable, see King, Sentana, and Wadhwani (1994).

this indicator is often much higher among smaller developed markets such as Belgium, Finland, etc. than among the largest economies. Finally, the industrial structure alignment is positive and statistically significant at the 5% level for smaller developed markets, indicating that structural changes in these countries have significant implications on their potential diversification benefits.

In summary, our results show that the increase in the relative importance of industry diversification in the 1990's comes not from any particular characteristic of the equity market at that time. Rather, it has its reflection in the interrelation between aggregate production growth rates across countries relative to those at the disaggregated, industry-specific level. These findings are particularly strong among developed countries. What contributes to this phenomenon? The most convincing argument for the increase in correlation at the aggregate production level is the ongoing economic integration process across countries, especially developed economies. At the disaggregated level, there is less evidence of common changes across all industries since they are less likely to be equally exposed to global economic conditions or global demands for specific products. In this respect, Carrieri, Errunza, and Sarkissian (2004) show that there could be differences in the level of financial integration between a country as a whole and some of its constituent industries. However, a thorough investigation of the reasons for the increased synchronization of production growth rates at the country level versus industry level is beyond the scope of this paper.

5. Conclusions

Many papers argue that benefits of international diversification come primarily from cross-country rather than cross-industry investments. However, increasing economic and political linkages among countries are likely to increase cross-country equity market correlations reducing the potential gains from international diversification. Do these integration processes lead to an equivalent increase in correlations across industries? We use a conditional framework and data from 17 OECD countries and show that they do not. We find that over the period of 1976-2003, the average conditional correlations across countries have increased in relation to those across industries and, unlike some other studies, show that this increase is not confined only to the late 1990's period.

Are there any economic forces that could be linked to the observed phenomenon? We first find that the on-going process of economic and financial convergence is accompanied by the significant alignment in the industrial structures of the U.S. and other countries. This process has substantially accelerated in the post-1990 period, indicating that real economic changes are likely to be responsible for the observed dynamics of the equity market correlations and industrial structure alignment. We show that our findings are related to an increase in the average correlation of aggregate production growth rates across countries relative to that of disaggregated production growth, especially among developed economies.

Finally, our results imply that portfolio managers should pay increasing attention to asset allocation across various industries in developed markets since changes in their equity market correlations at both country and industry levels are reflected on the real side of their economies. However, country-level investing should remain the predominant asset allocation approach in emerging markets.

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Table 1
Summary statistics: country- and industry-level equity returns

The table shows the following statistics: the mean, standard deviation, the Ljung-Box tests for autocorrelation of order twelve for raw returns and squared returns, $LB(z)_{12}$ and $LB(z^2)_{12}$, respectively, and the Bera-Jarque test for normality, BJ, as well as average unconditional cross-correlations, Ave CC. These statistics are shown for the U.S. dollar denominated equity market returns from the 17 OECD countries as well as the equally weighted averages of local industry returns for each industry group. The sample includes 336 monthly observations from January 1976 to December 2003. All the data are from Datastream. Some data are not available for certain countries or time periods. The last two columns in Panel A show the average cross-correlations of country equity returns and number of different industries per country. The last two columns in Panel B show the average cross-correlations of industry equity returns and the number of countries contributing to a given global industry. The returns are in percent per month. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Country equity returns

	Mean	S.D.	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	Ave CC	Industries
Austria	1.098	6.407	37.26 [a]	173.40 [a]	548.10 [a]	0.373	7
Belgium	1.141	5.394	12.64	16.42	70.76 [a]	0.443	8
Denmark	1.269	5.317	16.09	7.04	3.48	0.407	8
Finland	1.300	8.985	24.56 [b]	26.19 [b]	8.45 [b]	0.373	8
France	1.318	6.532	10.90	17.84	13.52 [a]	0.524	9
Germany	1.027	5.751	17.03	26.39 [a]	27.61 [a]	0.541	10
Greece	1.517	10.682	26.02 [b]	36.11 [a]	384.38 [a]	0.298	3
Ireland	1.536	6.708	18.68 [c]	36.14 [a]	23.37 [a]	0.427	7
Italy	1.197	7.565	22.55 [b]	22.66 [b]	13.11 [a]	0.409	10
Japan	1.028	6.565	18.80 [c]	27.25 [c]	10.84 [a]	0.268	10
Korea	1.036	12.048	11.52	30.40 [a]	297.97 [a]	0.222	9
Mexico	1.613	9.500	19.38 [c]	12.46	28.25 [a]	0.284	9
Portugal	0.642	5.692	13.28	14.02	0.42	0.413	7
Spain	1.103	6.264	20.33 [c]	9.86	19.04 [a]	0.509	9
Sweden	1.437	7.236	8.53	12.58	3.20	0.483	8
UK	1.316	5.618	8.33	20.70 [c]	16.87 [a]	0.477	10
US	1.149	4.396	9.86	7.79	64.76 [a]	0.373	10

Panel B: Averages of industry equity returns (excluding the U.S.)

	Mean	S.D.	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	Ave CC	Countries
Basic Industries	1.176	8.061	16.30	35.90 [a]	40.97 [a]	0.773	16
Cyclical Goods	0.841	9.590	12.35	17.02	429.45 [a]	0.704	12
Cyclical Services	1.167	7.953	17.64	27.46 [a]	76.53 [a]	0.791	15
Financials	1.268	8.076	20.00 [c]	42.97 [a]	416.36 [a]	0.766	16
General Industries	1.045	8.269	14.07	22.42 [b]	241.26 [a]	0.790	15
Inform. Technology	1.729	12.247	21.95 [b]	36.57 [a]	236.98 [a]	0.571	9
Non-Cyclical Goods	1.217	8.180	15.04	23.50 [b]	1801.70 [a]	0.731	16
Non-Cyclical Services	1.670	9.683	17.03	22.25 [b]	97.46 [a]	0.646	12
Resources	1.271	10.035	20.35 [c]	25.12 [b]	325.30 [a]	0.641	10
Utilities	1.369	8.230	12.89	20.91 [c]	225.12 [a]	0.627	11

Table 2
Summary statistics: country- and industry-level industrial production growth

The table shows the following statistics: the mean, standard deviation, the Ljung-Box tests for autocorrelation of order twelve for raw returns and squared returns, $LB(z)_{12}$ and $LB(z^2)_{12}$, respectively, and the Bera-Jarque test for normality, BJ (Panels A and B), as well as unconditional cross-correlation (Panels C and D). These statistics are shown for the seasonally adjusted aggregate industrial production growth rates from the 17 OECD countries as well as the equally weighted averages of their disaggregated industrial production growth rates for each industry group. The sample includes 216 monthly observations from January 1986 to December 2003. The data are from Datastream. Some data are not available for certain countries or time periods. The last two columns in Panel A show the average cross-correlations of country-level industrial production growth rates and the number of industry-level industrial production growth rates per country. The last two columns in Panel B show the average cross-correlations of industry-level industrial production growth rates and the number of countries that have given industry-level industrial production data. The industrial production growth is in percent per month. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Country-level industrial production growth

	Mean	S.D.	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	Ave CC	Industries
Austria	0.311	2.172	72.16 [a]	15.84	6.25 [b]	0.057	6
Belgium	0.156	2.627	132.61 [a]	42.49 [a]	14.10 [a]	0.091	8
Denmark	0.185	3.519	54.35 [a]	45.66 [a]	138.96 [a]	0.081	8
Finland	0.350	2.996	57.53 [a]	23.63 [b]	361.27 [a]	0.097	9
France	0.119	1.016	56.57 [a]	39.04 [a]	10.50 [a]	0.087	8
Germany	0.135	1.345	43.18 [a]	35.12 [a]	6.07 [b]	0.054	9
Greece	0.110	3.044	62.28 [a]	27.41 [a]	1585.7 [a]	0.016	9
Ireland	0.950	4.574	76.45 [a]	48.05 [a]	56.71 [a]	0.049	9
Italy	0.134	1.101	32.55 [a]	65.67 [a]	64.72 [a]	0.116	9
Japan	0.109	1.361	38.60 [a]	11.36	2.18	0.049	10
Korea	0.659	1.888	17.30	17.13	1.87	0.059	10
Mexico	0.235	1.265	27.43 [a]	26.53 [a]	19.96 [a]	0.011	2
Portugal	0.273	2.809	79.30 [a]	70.48 [a]	45.09 [a]	0.032	9
Spain	0.185	1.884	69.66 [a]	47.42 [a]	49.97 [a]	0.095	9
Sweden	0.236	2.362	51.08 [a]	25.93 [b]	17.86 [a]	-0.016	9
UK	0.106	0.921	48.84 [a]	13.68	160.99 [a]	0.100	9
US	0.231	0.511	72.12 [a]	7.90	0.15	0.100	N/A

Panel B: Averages of industry-level industrial production growth (excluding the U.S.)

	Mean	S.D.	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	Ave CC	Countries
Basic Metals	0.255	4.965	46.76 [a]	32.41 [a]	74.04 [a]	0.221	15
Chemicals	0.489	4.304	49.00 [a]	21.29 [b]	116.33 [a]	0.228	15
Electrical Equipment	0.568	6.793	51.35 [a]	42.32 [a]	425.57 [a]	0.175	13
Food	0.147	1.692	63.34 [a]	25.81 [b]	9305.04 [a]	0.140	13
Machinery	0.334	5.922	45.20 [a]	27.45 [a]	612.54 [a]	0.192	15
Mining	-0.046	1.902	32.94 [a]	20.43 [c]	581.38 [a]	0.090	3
Pulp & Paper	0.278	3.591	43.61 [a]	16.59	569.63 [a]	0.209	15
Textiles	-0.051	4.533	50.77 [a]	34.35 [a]	319.11 [a]	0.249	15
Transport Equipment	0.452	7.088	49.82 [a]	23.73 [b]	323.21 [a]	0.047	14
Utilities	0.276	3.722	40.02 [a]	23.21 [b]	96.50 [a]	-0.012	15

Table 3
Residual diagnostics for equity returns

The table shows the following return residual diagnostics: the Ljung-Box tests for autocorrelation of order twelve for residuals and squared residuals, $LB(z)_{12}$ and $LB(z^2)_{12}$, respectively, the Bera-Jarque test for normality, BJ, and the Engel-Ng test (t-stat) for negative asymmetry, EN. These statistics are shown for the U.S. dollar denominated equity market returns for the 16 OECD countries (Panel A) as well as the equally weighted averages of local industry returns for each industry group (Panel B). The sample includes 336 monthly observations from January 1976 to December 2003. All the data are from Datastream. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Country equity returns

	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	EN
Austria	13.58	17.31	55.84 [a]	-0.47
Belgium	7.83	7.22	56.56 [a]	-0.97
Denmark	14.78	4.00	1.54	-0.04
Finland	23.63 [b]	13.40	1.34	0.56
France	10.06	4.55	6.78 [b]	-0.91
Germany	15.28	6.43	16.38 [a]	-0.47
Greece	10.06	4.54	6.79 [b]	-0.91
Ireland	17.81	7.80	23.98 [a]	0.59
Italy	19.36 [c]	4.30	9.68 [a]	0.77
Japan	14.98	15.35	4.27	1.05
Korea	7.98	5.92	4.05	-0.81
Mexico	18.08	12.96	24.00 [a]	0.66
Portugal	13.40	11.34	0.03	0.82
Spain	19.05 [c]	4.81	20.51 [a]	-0.98
Sweden	8.20	2.31	2.94	0.60
UK	6.12	6.08	16.90 [a]	-0.29

Panel B: Averages of industry equity returns (excluding the U.S.)

	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	EN
Basic Industries	13.45	10.66	17.54 [a]	-0.02
Cyclical Goods	10.81	11.40	59.44 [a]	-0.13
Cyclical Services	14.58	11.23	24.43 [a]	0.03
Financials	13.73	10.63	54.55 [a]	-0.31
General Industries	11.24	8.19	61.06 [a]	0.16
Inform. Technology	18.12	13.67	22.96 [a]	-0.04
Non-Cyclical Goods	11.00	9.79	116.04 [a]	-0.11
Non-Cyclical Services	14.57	10.73	66.83 [a]	0.00
Resources	14.93	9.44	24.70 [a]	-0.35
Utilities	8.08	9.26	146.83 [a]	-0.13

Table 4
Tests on correlation trends in equity returns

The table shows the average point estimates of the trend coefficients in cross-correlations of U.S. equity market index returns with country and industry-level equity returns for 16 OECD countries. There are 130 series of industry-level equity return correlations. The average p-values are in parentheses. It also reports the total numbers of negative and positive trend coefficients, as well as those with statistical significance at the 10% level or smaller (marked with a star).

		Negative trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
Country-level EQ:							
All countries	5.544 (0.122)	0	N/A	0	16	5.544 (0.122)	8
Large Developed	3.325 (0.199)	0	N/A	0	5	3.325 (0.199)	1
Small Developed	2.896 (0.095)	0	N/A	0	7	2.896 (0.095)	4
Emerging	12.959 (0.074)	0	N/A	0	4	12.959 (0.074)	3
Industry-level EQ:							
All countries	5.756 (0.307)	12	-1.257 (0.608)	1	118	5.374 (0.285)	27
Large Developed	5.309 (0.286)	3	-0.374 (0.506)	0	45	5.680 (0.272)	17
Small Developed	4.163 (0.322)	6	-2.062 (0.612)	1	46	4.958 (0.284)	15
Emerging	9.549 (0.315)	3	-0.530 (0.704)	0	27	9.963 (0.315)	8

Table 5
Residual diagnostics for industrial production growth

The table shows the residual diagnostics of the industrial production growth: the Ljung-Box tests for autocorrelation of order twelve for residuals and squared residuals, $LB(z)_{12}$ and $LB(z^2)_{12}$, respectively, the Bera-Jarque test for normality, BJ, and the Engel-Ng test (t-stat) for negative asymmetry, EN. These statistics are shown for the country-level industrial production growth for the 16 OECD countries (Panel A) as well as the equally weighted averages of local industry-level industrial production for each industry group (Panel B). The sample includes 168 monthly observations from January 1986 to December 2003. All the data are from Datastream. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Country-level industrial production growth

	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	EN
Austria	42.36 [a]	21.02 [b]	12.72 [a]	-0.40
Belgium	14.04	13.01	10.68 [a]	0.24
Denmark	42.06 [a]	21.41 [b]	194.88 [a]	0.59
Finland	16.56	6.65	18.68 [a]	-0.96
France	23.36 [a]	5.87	1027.44 [a]	-0.89
Germany	23.06 [a]	7.76	23.53 [a]	0.49
Greece	17.56	6.71	0.03	-0.90
Ireland	30.94 [a]	9.15	28.74 [a]	-0.87
Italy	17.27	10.11	19.02 [a]	0.48
Japan	16.66	16.55	9.55 [a]	-1.43
Korea	33.01 [a]	5.57	1.98	-1.09
Mexico	14.66	4.93	7.08	-0.56
Portugal	14.27	20.72 [b]	42.74 [a]	-0.39
Spain	12.43	3.44	35.15 [a]	-0.39
Sweden	16.86	16.70	16.43 [a]	0.22
UK	24.58 [a]	16.94	4.33	1.12

Panel B: Averages of industry-level industrial production growth (excluding the U.S.)

	$LB(z)_{12}$	$LB(z^2)_{12}$	BJ	EN
Basic Metals	18.66 [c]	13.25	64.37 [a]	-0.66
Chemicals	18.87 [c]	8.30	88.74 [a]	-0.46
Electrical Equipment	20.99 [c]	11.11	69.97 [a]	-0.26
Food	21.73 [b]	7.67	337.62 [a]	-0.08
Machinery	20.95 [c]	9.58	113.85 [a]	-0.59
Mining	20.30 [c]	6.25	503.86 [a]	-0.06
Pulp & Paper	20.91 [c]	8.93	87.00 [a]	-0.28
Textiles	18.22	12.12	71.37 [a]	-0.34
Transport Equipment	24.78 [b]	14.37	50.75 [a]	-0.89
Utilities	23.14 [b]	10.64	170.66 [a]	-0.13

Table 6
Tests on correlation trends in industrial production growth

The table shows the average point estimates of the trend coefficients in cross-correlations of U.S. aggregate industrial production growth with country and industry-level industrial production growth rates for the 16 OECD countries. There are 128 series of industry-level industrial production growth correlations. The average p-values are in parentheses. It also reports the total numbers of negative and positive trend coefficients, as well as those with statistical significance at the 10% level or smaller (marked with a star).

		Non-positive trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
Country-level IP:							
All countries	0.162 (0.356)	5	-0.176 (0.544)	0	11	0.316 (0.271)	3
Large Developed	0.049 (0.380)	2	-0.038 (0.744)	0	3	0.123 (0.266)	1
Small Developed	0.336 (0.290)	1	-0.371 (0.200)	0	6	0.389 (0.262)	1
Emerging	-0.011 (0.346)	2	-0.145 (0.344)	0	2	0.196 (0.177)	1
Industry-level IP:							
All countries	0.010 (0.478)	62	-0.361 (0.467)	9	66	0.354 (0.480)	6
Large Developed	-0.099 (0.439)	26	-0.275 (0.428)	6	18	0.185 (0.424)	3
Small Developed	0.120 (0.498)	24	-0.371 (0.510)	3	32	0.410 (0.498)	2
Emerging	-0.035 (0.499)	12	-0.530 (0.468)	0	16	0.436 (0.506)	1

Table 7
Industrial structure alignment

The table shows the proportion of market capitalization of each industry in the U.S. total equity market and the equally weighted average of similar proportions across all other countries in the sample over the two calendar periods, 1990-1996 and 1997-2003. It also gives the absolute difference in these measures for each sub-period (Diff), as well as its change from the first period to the second (Spread) with the corresponding t-statistic in the last column. All market capitalization data is from Datastream and are in U.S. dollars. The total number of industries is 142 (including ten in the U.S.). The data is in percentages.

Panel A: Country-level alignment

	1990-1996	1997-2003		
	Diff.	Diff.	Spread	t-stat
Austria	10.67	8.96	-1.71	-6.42
Belgium	10.22	10.45	0.23	1.70
Denmark	7.03	5.89	-1.13	-6.01
Finland	9.13	10.39	1.26	6.91
France	4.32	4.65	0.33	4.31
Germany	10.27	7.95	-2.32	-20.51
Greece	15.60	9.97	-5.63	-10.72
Ireland	10.63	10.07	-0.56	-3.50
Italy	10.77	9.76	-1.01	-12.66
Japan	6.40	5.66	-0.74	-7.39
Korea	9.76	9.62	-0.14	-1.08
Mexico	10.07	9.28	-0.79	-4.46
Portugal	13.93	12.17	-1.76	-8.90
Spain	9.28	9.69	0.41	4.88
Sweden	10.05	6.38	-3.67	-22.42
UK	3.94	5.00	1.06	11.65
Large Developed	7.14	6.60	-0.95	-7.82
Small Developed	9.57	8.83	-0.74	-4.19
Emerging	9.87	8.21	-2.19	-6.66
Average	9.50	8.49	-1.01	-5.12

Panel B: Industry-level alignment

	1990-1996			1997-2003				
	US	Others	Diff.	US	Others	Diff.	Spread	t-stat
Basic Industries	6.15	15.48	9.33	3.10	9.67	6.58	-2.76	-1.08
Cyclical Goods	3.87	4.36	0.49	2.02	3.47	1.45	0.96	2.06
Cyclical Services	13.00	8.40	4.60	13.32	10.11	3.21	-1.39	-2.22
Financials	12.57	30.51	17.95	18.82	27.35	8.54	-9.41	-5.50
General Industries	8.76	9.69	0.94	8.26	8.31	0.05	-0.89	-1.28
Inform. Technology	9.11	6.27	2.84	18.71	7.80	10.91	8.07	7.65
Non-Cyclical Goods	22.38	9.37	13.01	19.95	9.51	10.44	-2.57	-2.61
Non-Cyclical Services	8.91	11.86	2.94	6.96	15.50	8.55	5.60	3.84
Resources	8.28	5.08	3.20	5.43	5.22	0.20	-3.00	-4.25
Utilities	6.96	10.80	3.83	3.43	7.62	4.18	0.35	0.42
Average		11.18	5.91		10.46	5.41	-0.50	-0.43

Table 8
Tests for common trends between correlation spreads in equity returns and industrial production growth

The table shows the results of Wald tests for common deterministic trend slopes between correlation spreads in returns and industrial production growth based on Vogelsang and Franses (2004) using the Bartlett kernel with two variations of the bandwidth for the HAC estimator: constant and automatic. The sample period is 1986-2003 (October 1987 to December 2003 for emerging markets). The constant bandwidth is the sample size, while the automatic bandwidth is modeled based on an AR(1) process as in Andrews (1991). The p-values are in parentheses. LD, SD, and EM stand for the largest developed, smaller developed, and emerging markets, respectively. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

	All	LD	SD	EM	LD, SD, EM	LD, SD
Constant bandwidth	4.654^{b} (0.031)	0.007 (0.933)	2.772^{c} (0.096)	3.090^{c} (0.073)	36.784^{a} (0.000)	6.559^{c} (0.087)
Automatic bandwidth	4.739^{b} (0.029)	0.007 (0.933)	2.772^{c} (0.096)	7.104^{a} (0.008)	35.701^{a} (0.000)	6.304^{c} (0.098)
Degrees of freedom	1	1	1	1	5	3

Table 9
Relation between correlation spreads in equity returns and industrial production growth

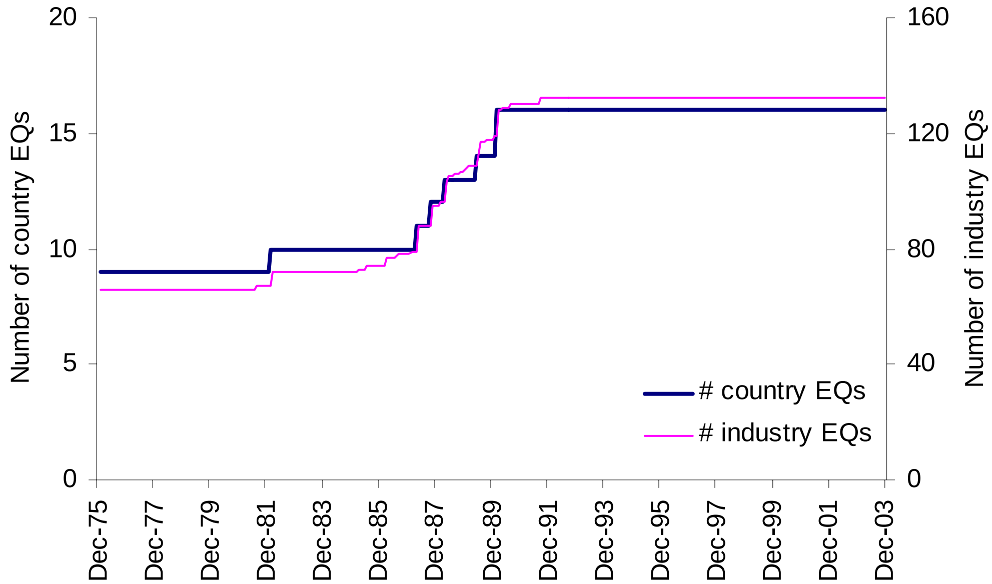
The table shows the relation between correlation spread in returns (EQ spread) and industrial production growth (IP spread), as well as the variables that proxy industrial structure alignment (IS alignment), financial development and market openness. The sample period is 1986-2003 (October 1987 to December 2003 for emerging markets). Panel A reports the auto- (ρ) and cross-correlations of all the variables. Panel B shows the results from the robust regression with HAC standard errors and automatic lag selection of the correlation spread in equity returns (EQ spread) on the correlation spread in industrial production and other three variables. Financial development is the average ratio of equity market capitalization to GDP in the 17 OECD countries and enters the regression in terms if its month-to-month changes. Market openness is the average ratio of the sum of exports and imposts to GDP in the 17 OECD countries. The industrial structure alignment measure is inverted. All variable are detrended. The p-values are in parentheses. LD, SD, and EM stand for the largest developed, smaller developed, and emerging markets, respectively. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively. The intercepts in the regressions are identical to zero and therefore are not reported.

Panel A: Auto- and cross-correlations

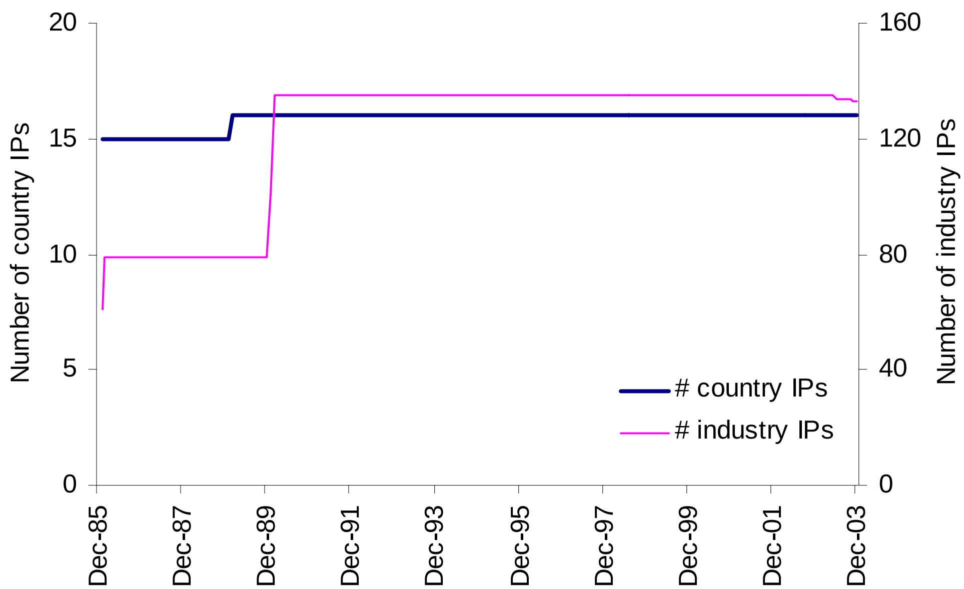
		Cross-correlations			
	ρ	IP Spread	IS alignment	Financial devel.	Market openness
EQ spread	0.965	0.749	0.746	0.788	0.799
IP spread	0.752	1	0.686	0.692	0.669
IS alignment	0.983		1	0.655	0.741
Financial develop.	0.993			1	0.830
Market openness	0.819				1

Panel B: Regression results with detrended series

	(1)	(2)	(3)	(4)	(5)	(6)
	LD	SD	EM	LD	SD	EM
IP spread	-0.014	-0.019	0.021	-0.003	-0.020	0.019
	(0.711)	(0.599)	(0.412)	(0.939)	(0.544)	(0.453)
IS alignment				-0.942	1.539 [b]	0.048
				(0.446)	(0.023)	(0.930)
Δ Financial development				-0.039	-0.018	-0.011
				(0.159)	(0.391)	(0.729)
Market openness				0.142 [c]	-0.005	0.108 [b]
				(0.083)	(0.890)	(0.028)
Adj R^2 (%)	0.05	0.18	0.23	3.48	8.73	4.05

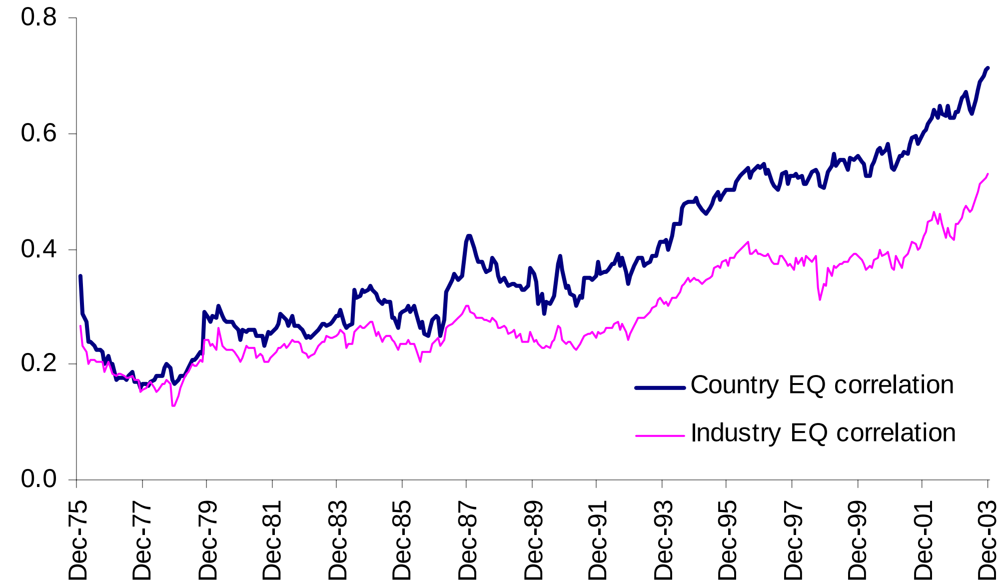


A



B

Figure 1. Frequency of observations. The plot depicts the numbers of series across countries and industries contributing to the sample of observations over time. Plot A covers the equity return series and Plot B covers the industrial production growth series.



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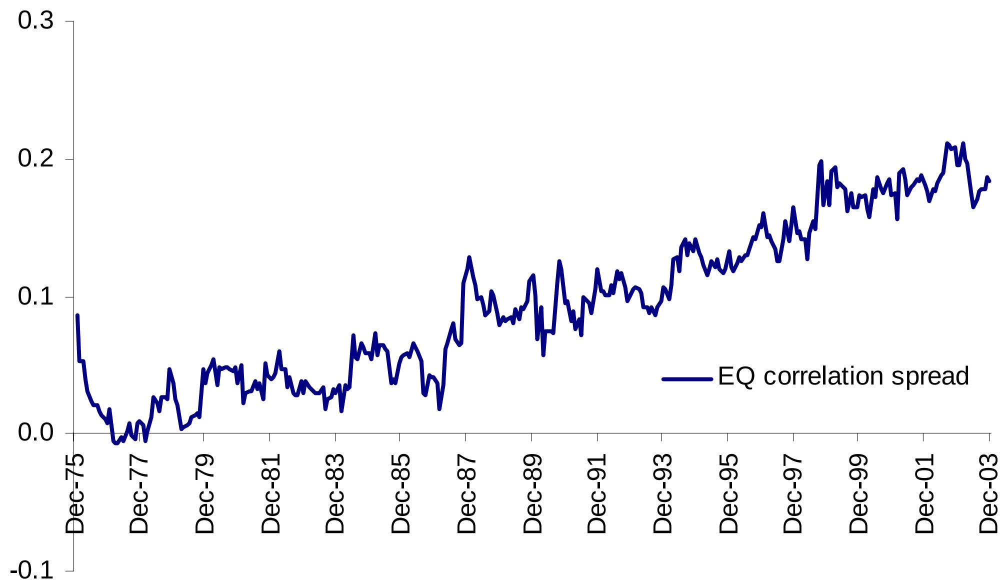


B

Figure 2. Average pairwise conditional correlations of equity returns. Plot A depicts three average pairwise conditional correlations between the U.S. equity market index returns and the different return series groups. The first one is the aggregate country correlation using equity indexes of all the 16 OECD countries (Country EQ correlation). The second is the disaggregated industry correlations based on indexes of local industries, excluding the U.S. (Industry EQ correlation). Plot B shows the spreads between the two correlation series.

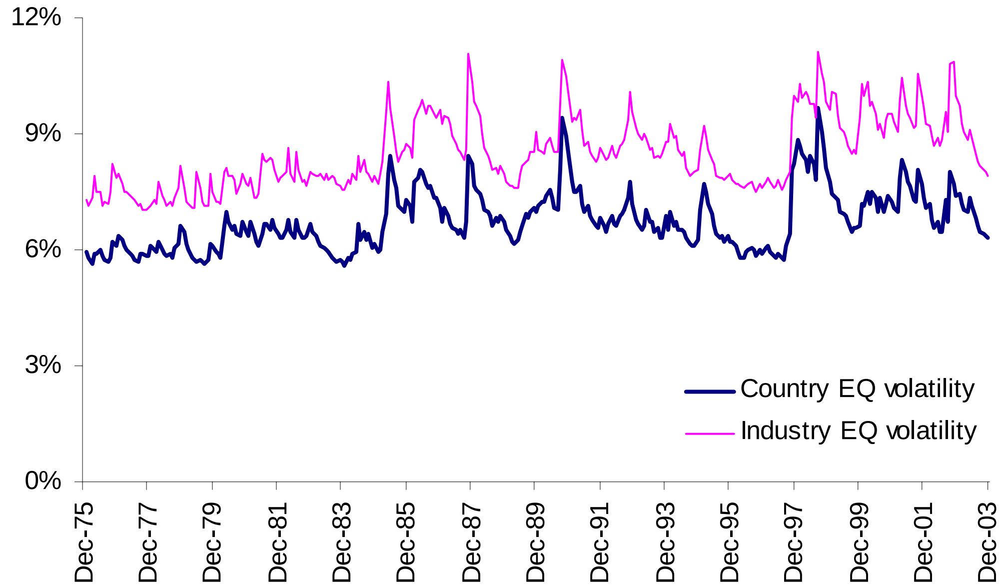
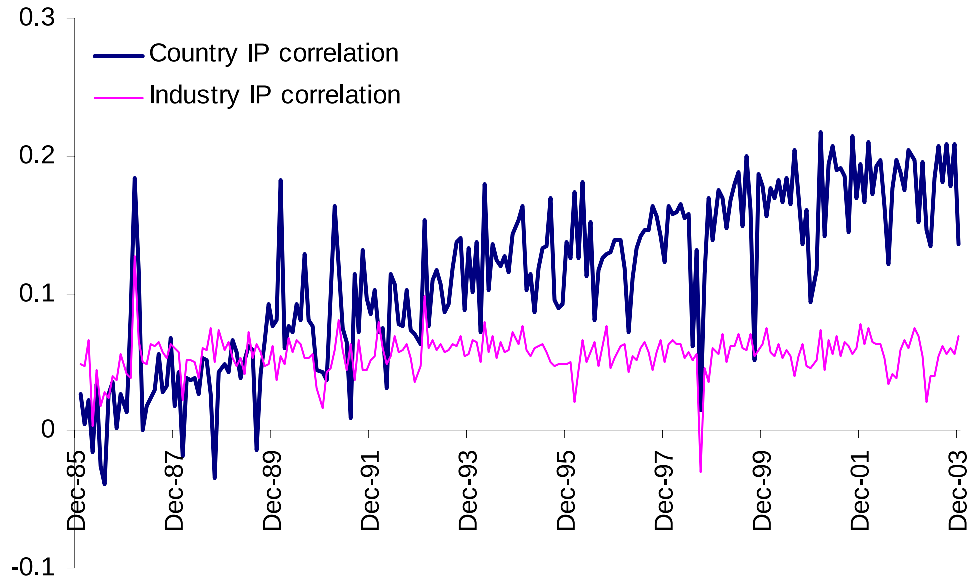
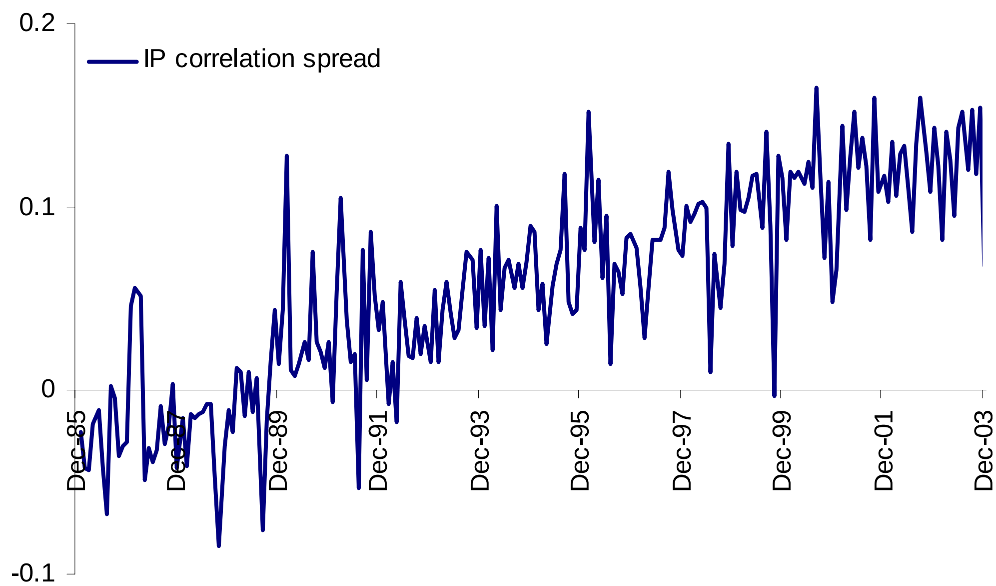


Figure 3. Volatility dynamics of equity returns. The figure depicts the dynamics of conditional volatility of equity returns over the entire sample period. It plots the average volatilities across 16 OECD countries, excluding the U.S. (Country EQ volatility) and all industries (Industry EQ volatility).



A



B

Figure 4. Average pairwise conditional correlations of industrial production growth. Plot A depicts average pairwise conditional correlations between the U.S. aggregate industrial production growth and two other industrial production series. The first is the aggregate industrial production growth rates of all the countries in the sample (Country IP correlation). The second is the disaggregated industrial production growth rates, excluding those in the U.S. (Industry IP correlation). Plot B shows the spread between the two series (IP correlation spread).

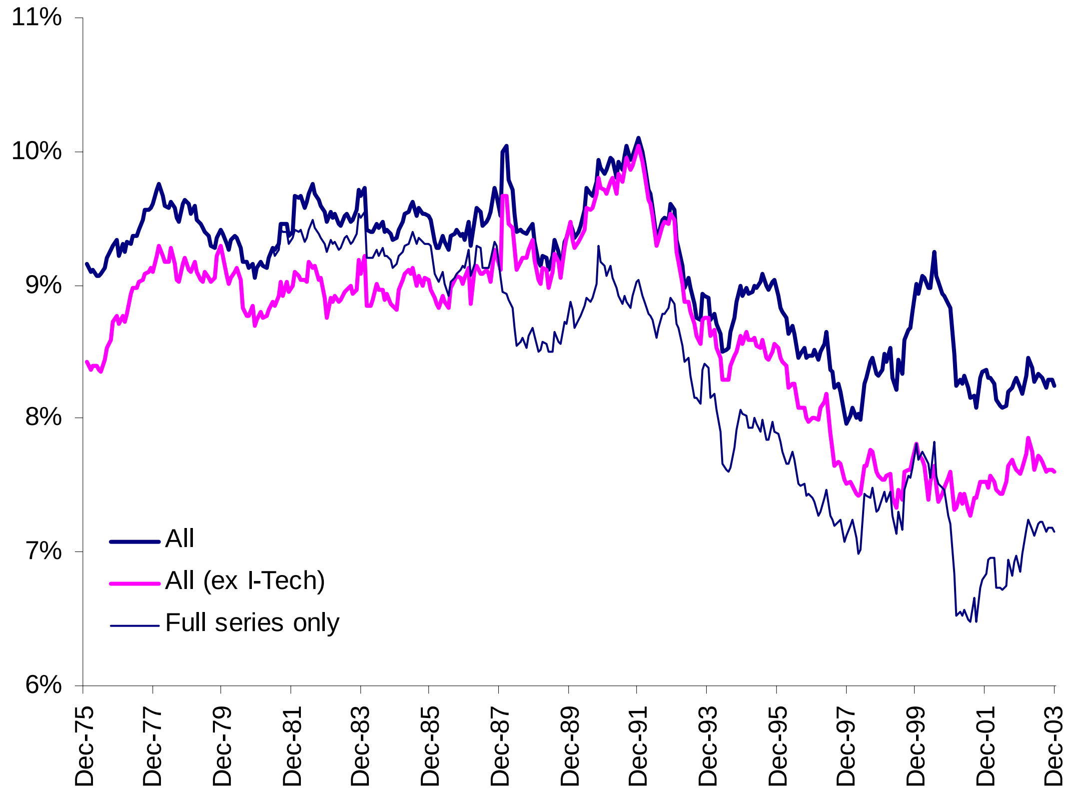
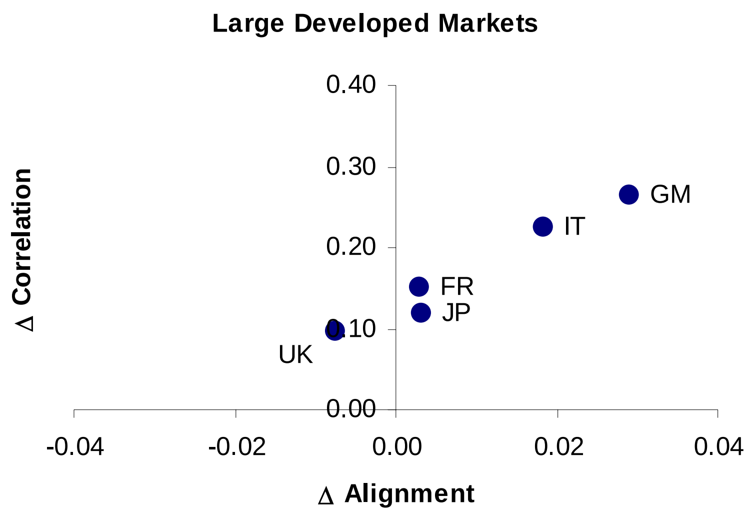
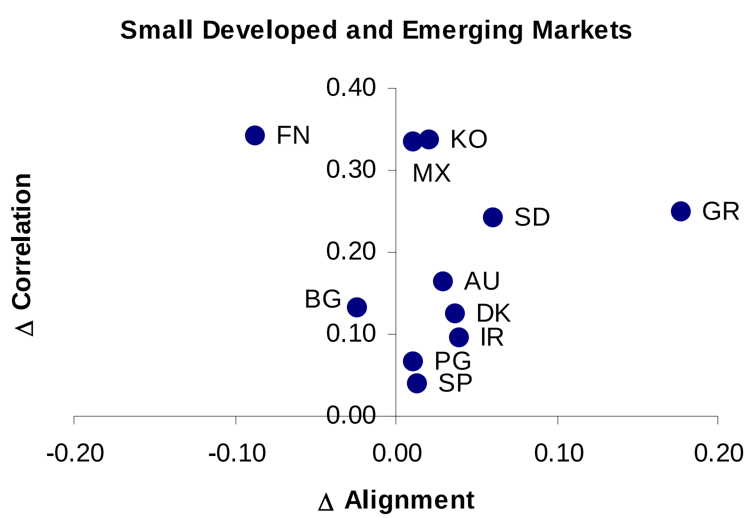


Figure 5. Industrial structure alignment. The figure depicts the time variation in the industrial structure alignment between the U.S. and other countries. At each month the alignment is computed by taking the average absolute difference between each industry proportion in the U.S. market capitalization on one side and each of the remaining 16 countries on the other. The plot shows the dynamics of average alignment across all countries and industries, of all the series excluding information technology sector, as well as of those series that existed during the entire sample period (66 in total).

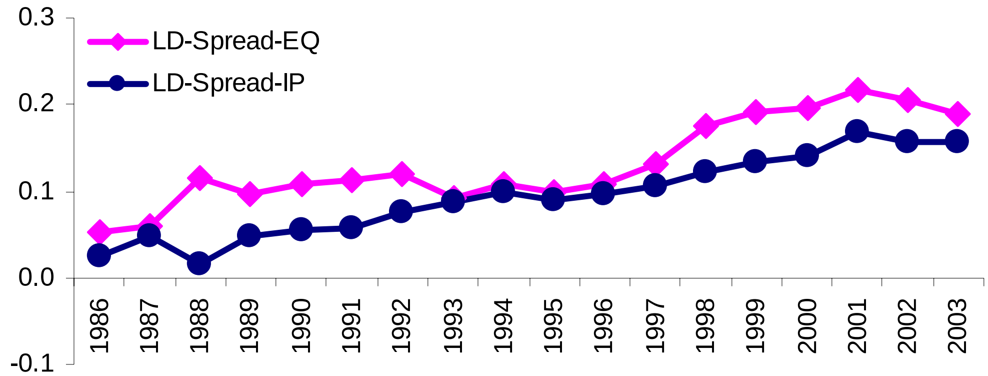


A



B

Figure 6. Changes in correlations of equity returns and industrial structure alignment. The figure depicts the relation between the changes in the country-level equity return correlations and changes in industrial structure alignment from 1986-1990 to 1998-2003. At each month, the alignment for a given country is computed by taking the average absolute difference (with a negative sign) between each industry proportion in that country's market capitalization on one side and the corresponding industry in the U.S. market on the other. Plot A depicts the relation for five largest developed markets, Plot B – for the set of seven small developed and four emerging markets.



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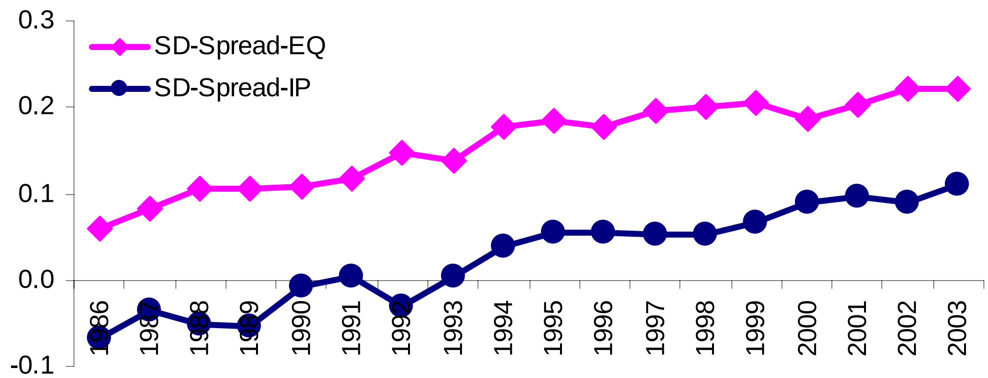

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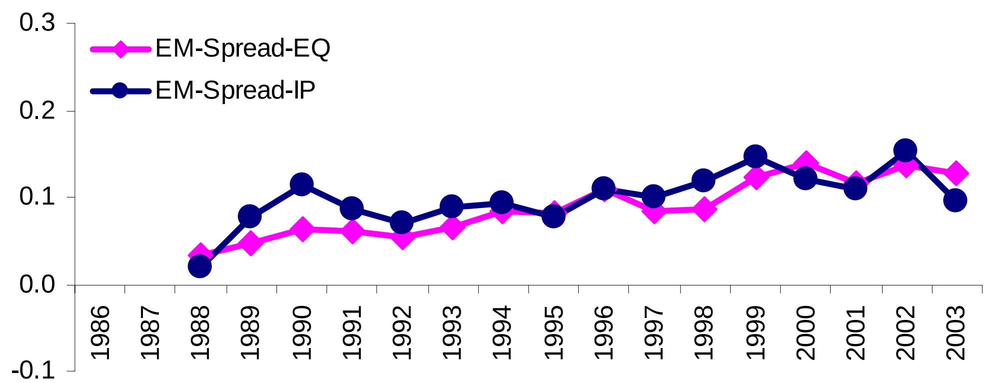

C

Figure 7. Correlation spreads for equity returns and industrial production growth for different country groups. The figure depicts the two average annual spreads in conditional correlations. The first is one is between the U.S. equity market index returns on one side and the returns on equity market indexes or their corresponding local industry indexes on the other. The second one is between the U.S. aggregate industrial production growth on one side and aggregate industrial production growth rates or their corresponding disaggregated production growth rates on the other. Plot A depicts the two series for the largest developed economies, Plot B – for smaller developed countries, and Plot C – for emerging countries.