Industrial Structure, Market Integration, and International Portfolio Diversification

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ABSTRACT

Roll (1992) suggests that industrial composition explains substantial cross-country variation in stock market returns. We observe an increasing convergence in the industrial structure between the U.S. and 16 other OECD countries and then examine its implications on co-movements in global equity markets and countries' real output. We find that the average conditional correlation across countries has increased in relation to that across industries for both equity returns and industrial production growth, especially among large developed countries. Our findings establish the links between the dynamics of industrial structure, equity returns, and industrial production growth and imply increased benefits of industry-level investing across large developed markets.

JEL classification: F15; G15

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1. Introduction

There is a wide consensus that countries are becoming more integrated. The impact of this process on countries' industrial structure is directly relevant to our understanding of the dynamics of equity market returns and cross-country correlations. Roll (1992) suggests that industrial composition can explain substantial variation in national stock returns stating that "*two countries will be more highly correlated if their industrial makeups are similar*" (p.37). Yet, Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) find that industrial structure accounts for a very small proportion of variation in national stock market returns. On the other hand, Forbes and Chinn (2004) find that cross-country trade is the most important determinant of stock market movements around the world. In addition, there is substantial evidence that the correlations among international equity returns have been changing overtime (e.g., see Erb et al., 1994; Karolyi and Stulz, 1996; Longin and Solnik, 2001; and Ang and Bekaert, 2002). As a result, any shift in the industrial structure across countries in response to ongoing economic and financial integration must impact global linkages and may also lead to long-term changes in their real economies.

The literature offers two opposite views on the impact of trade and economic integration on country's industrial structure: specialization and diversification. The proponents of the first view, such as Krugman (1991), Kalemli-Ozcan et al. (2001), and others argue that economic and financial integration leads to industrial specialization. They claim that lower barriers to trade and free flow of capital across markets will induce countries to specialize more, leading to less synchronous output fluctuations. The supporters of the second view, such as Frankel and Rose (1998), Davis (2003), and other authors, state that trade integration helps diversify production structures. Several papers also advocate a non-linear relation between integration and industrial structure. Krugman and Venables (1995) and Puga (1999) show that while partial economic integration leads to more specialization, deep integration with substantially reduced transportation costs but limited labor mobility makes firms increasingly sensitive to wage differentials, leading to industrial diversification.[1] Finally, Ishikawa (1992) shows that economic growth is accompanied by changes in industrial structure and changes in industrial composition of the manufacturing sector accelerate economic growth.

Thus, this paper builds a bridge between the finance and the economics literature and provides a new framework to analyze the dynamics of global linkages. There are few papers that attempt to link real and financial sectors of the economy. For instance, Backus et al. (1992) develop the international real business cycle model with perfectly integrated goods and financial markets across countries. Yet, the model generates much lower aggregate output correlations than is observed empirically. On the other hand, Dumas et al. (2003) provide an alternative framework to measure the degree of commonality of country industrial output and equity market returns and conclude that the observed correlations are consistent with integrated markets.

Our paper has two goals. First, we examine whether the alignment in the industrial structure between the United States and other OECD countries has changed over time. Previous studies use low frequency (usually annual) proxies for sectoral concentration data such as employment or value added per sector (e.g., see Krugman, 1991; Imbs and Wacziarg, 2003). Both of these variables have major drawbacks. The employment data may attach too much importance to labor-intensive firms (industries) at the expense of other firms (industries) in a country's economy.[2] The procedure of calculating the value added of industry and services varies across countries and over time for most countries. More importantly, most of the earlier studies focus on how diversified a country is, but not how close two countries are to each other sector by sector. Our proxy for industrial structure is more precise and objective: we use the

[1] Imbs and Wacziarg (2003), on the contrary, argue that production specialization is a U-shaped function of country's economic development. Countries first diversify, but relatively late in their development process, they start specializing again. Their result however does not account for integration level across countries.

[2] For instance, as of September 2006, Google, an IT-company, and Chevron, an integrated oil and gas company, both had a market capitalization of about $140bln. Yet, Google employed only around 8,000 people, while Chevron – 47,000.

relative capitalization of a given industry in the country's total market capitalization and deal with monthly data.[3]

Second, we study the impact of industrial structure dynamics on global linkages of both the stock market and the real economy. To this end, we use country and industry-level stock market returns and aggregate and disaggregated industrial production data and study changes in correlation between the U.S. and the other OECD countries. Even though industrial production does not cover the entire real economy, especially in developed markets, Bernanke and Mihov (1998) observe that at the monthly frequency, manufacturing output is a very close proxy for the overall GDP. Using the estimated correlations as proxies for the diversification potential at the country and industry levels, we relate our findings to the benefits of international portfolio diversification.

In our analysis, we take the U.S. perspective and consider the U.S. as a base country. Using data on industry-level equity capitalization from the U.S. and 16 other OECD countries over 1976-2003, we first document an increased alignment in the industrial structure between the U.S. and other countries that started at the beginning of 1990's. The average absolute difference between each sector's representation in the U.S. and other countries' markets is significantly larger in the first than in the second sub-period. The industrial structure alignment is present in 11 out of 16 countries.

We examine the implications of increased industrial structure alignment on both the financial side and the real side of the global economy using a conditional framework. We apply a similar procedure, a bivariate GARCH(1,1) model, to both equity return and industrial production data to allow comparison of results across the two estimations. We find that the average conditional return correlation between the U.S. and other OECD countries has increased gradually since the late 1980's. We also find an increase in the average conditional

[3] The market capitalization based proxy for industrial structure has been widely used in prior studies (e.g., see Roll, 1992; and Heston and Rouwenhorst, 1994).

correlation of aggregate production growth across countries, especially among large developed economies.

Our results show that countries that have high stock market correlations with the U.S. also have higher correlation with the U.S. output. More interestingly, among large developed countries, we also find a positive and significant relation between changes in the alignment of the industrial mix and changes in their equity market correlations with the U.S. This result is a unique empirical confirmation of Roll's (1992) argument that increased industrial alignment among countries should increase their cross-market return correlations. Furthermore, the observed pattern is mirrored on the real economy side, as we find that the increased alignment in the industrial structures of large developed countries with that of the U.S. also has a positive impact on their output growth correlations.

We then repeat the same GARCH(1,1) estimation at the disaggregated level but find that industry return and disaggregated industrial production correlations do not increase by the same amount as those based on the aggregate data. With respect to the portfolio allocation issue, this implies that industry level investing over time has become more important *relative* to country level allocation. Since the industrial structure of developed country return indices has become more similar to the U.S., country diversification is less effective and U.S. investors should pay more attention to the industrial make-up of their globally diversified portfolios.

Thus, our overall findings provide support for the diversification impact of the ongoing economic integration on industrial structure in large developed markets. They imply that deep economic integration has led large developed countries to diversify rather than specialize with respect to their industrial make-up, consistent with Krugman and Venables (1995), Frankel and Rose (1998), and others. Furthermore, similar to Rajan and Zingales (1998), Barth and Ramey (2001), and Dedola and Lippi (2005), our results suggest that monetary and other government policies have a heterogeneous impact on different sectors of integrated countries. This implies that the increasing benefits of industry-level investing across large developed countries that we document find support in the real side of their economies. Thus, our findings provide a new look at the current debate on country versus industry style in portfolio diversification.

The paper is organized as follows: Section 2 summarizes the stock market and industrial production growth data at the aggregate and disaggregated levels. Section 3 is devoted to the analysis of changes in the industrial structure in OECD countries vis-à-vis that of the U.S. during our sample period. Section 4 introduces the conditional methodology. Section 5 provides the estimation results for stock markets and production growth rates. In this section, we also establish the links between the dynamics of industrial structure, equity returns, and industrial production growth. Section 6 relates our findings to international portfolio diversification. Section 7 discusses robustness issues. Section 8 concludes.

2. Data

We work with two datasets. The first one contains country-level and sector-level equity returns while the second contains aggregate and disaggregated industrial production growth rates. Industrial production is especially useful for the purpose of our paper since, unlike many other macroeconomic variables, it is observable at the monthly frequency not only at the aggregate but also at the disaggregated level.[4] Throughout the paper, we use equally-weighted averages of equity returns and output growth data to have a meaningful comparison of results between the two datasets at both aggregate and disaggregated levels.[5]

2.1. Equity Data

[4] Previous studies have identified industrial production growth as an important variable linked to equity returns. It is one of the risk factors in the arbitrage pricing model of Chen et al. (1986). Fama (1981, 1990) finds that stock returns are highly correlated with future industrial production growth. Dumas et al. (2003) provide a theoretical framework where cross-country equity market correlations are modeled as a function of output correlations.
[5] There is no clear approach on value-weighted aggregation of the disaggregated industrial production growth that circumvents the issue of data comparability across industries and countries.

We use monthly returns on Global Equity indices 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. All country returns are converted into U.S. dollars using the corresponding exchange rates.

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 0.54 for Germany. 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 only four industry series available.

These country level indices are aggregated from ten sector indices. Our set of sectors consists of 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 industry indices practically span the entire equity market in each country. Panel B of Table 1 shows the summary statistics for disaggregated (local) industry returns. To help with the exposition of the large amount of local industry data, we aggregate the returns into averages for each industry group excluding the U.S. 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 highest 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.

Our sample does not cover a larger set of countries because data on local industry indexes and disaggregated economic variables are not available for a number of countries, including some developed ones. In addition, not all countries and sectors have data during the entire sample period. For instance, the total number of local sectors across all the countries excluding the U.S. is 132, and the corresponding number of sectors with market capitalization data available during our entire sample period is 66.[6] The most significant increase in the cross-section of our asset returns occurs at the beginning of the 1990's, when the data series for several developing countries become available both for equity returns and for sector weights. This is the main motivation to focus on the post-1990 sample in many of our tests.

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.[7] We consider

[6] 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.

[7] Datastream reports each observation for industrial production in the middle of the month.

aggregate industrial production growth rates for each country and use it as a proxy for the entire economic activity in a given country. Bernanke and Mihov (1998, page 881) show that at the monthly frequency, manufacturing output is a very close proxy for the overall GDP, even though it does not include the service sectors.

Table 2 provides summary statistics for 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 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 levels are substantially lower than cross-correlations among equity market returns in Table 1.

Panel B of Table 2 shows the summary statistics for the disaggregated industrial production growth rates. Also in this case, for ease of exposition, we present 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 smallest 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.

Similar to equity returns, the largest increase in the cross-section of these data occurs at the beginning of the 1990's. 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 leads us to compare the dynamics between the two series primarily in the post-1990 period.

3. The Dynamics of Industrial Structure

3.1. Theories of Economic Integration and Industrial Structure

There are two opposite views on the impact of economic integration processes on a country's industrial structure: specialization or diversification. The first set of studies, starting with the seminal paper by Krugman (1991), argues that economic integration through trade leads to industrial specialization. These studies show that lower trade and transportation barriers will induce countries to specialize, thus, making output fluctuations less synchronous. The second set of studies, such as Frankel and Rose (1998) and Davis (2003), state that trade integration helps diversify production structures. Frankel and Rose (1998) argue that the removal of trade barriers leads to more correlated economic policies and business cycles due to easier spread of demand shocks across national borders as well as knowledge and technology spillovers. Davis (2003) shows that if homogeneous goods have identical transportation costs, then the increased economic integration is unlikely to leave some countries at a disadvantage relative to other, larger and industrially more diverse countries. Yet, another stance on the relation between economic integration and industrial structure is that it is non-linear. Krugman and Venables (1995) and Puga (1999) show that some economic integration and a reduction in transportation costs increases specialization across countries. However, more profound cross-market integration reduces transportation costs further and, with limited labor mobility, it induces firms to be increasingly sensitive to wage differentials, thus, leading the countries to industrial diversification.

The more correlated the economic policies and business cycles are between the two countries the more correlated their equity market returns will be, *ceteris paribus*. Indeed, if different countries become more specialized in production of different goods and services, then their economies become less similar to each other.[8] Therefore, *ceteris paribus*, the correlations between equity markets of these countries are also less likely to increase over time (see Roll, 1992).[9] We do not take a priori stand on this issue but rather expect our data to give some support in favor of either specialization or diversification hypothesis.

3.2. Industrial Structure Convergence

We first investigate country level industrial alignment by looking at the average changes in the industrial composition of countries relative to that of the U.S. over the entire sample period. Our focus on OECD countries allows us to examine industrial structure changes among a set of countries that are relatively well integrated. For each month, the average industrial structure alignment (ISA) between the U.S. and other countries is computed as the sum of absolute differences 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, namely:

$$ISA_t = \sum_j \sum_i \left| \frac{MkCap_{i,t}^j}{MkCap_t^j} - \frac{MkCap_{i,t}^{US}}{MkCap_t^{US}} \right|, \tag{1}$$

where $MkCap_{i,t}^j$ and $MkCap_{i,t}^{US}$ are the industry *i*'s capitalization in country *j* and the U.S., while $MkCap_t^j$ and $MkCap_t^{US}$ are the total market capitalization of country *j* and the U.S. at time *t*, respectively.[10]

Figure 1 shows the time-series of our alignment measure. It presents the dynamics of the average alignment across all countries and industries as well as only those based on the

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8 Campa and Fernandes (2006) show that country level of industrial specialization affects the magnitude of country and industry shocks.

9 The evidence of increasing equity market correlations in the 20th century, especially among developed markets, presented by Goetzmann et al. (2005) and Longin and Solnik (1995) seems to provide little ground to back up production specialization.

10 One of the commonly used measures in many studies on industrial structure is the Herfindahl index. However, it is not a useful alternative to our measure of cross-country industry structure alignment because it measures the industrial diversification within a country, while we are interested in how close the two countries' industrial structures are relative to each other.

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 among U.S. and other markets. 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. Hence, we plot the alignment structure based only on those series that existed during the entire sample period, and it confirms our previous result. It is worth pointing out that this smaller sample contains predominantly the largest developed countries.

We now examine the extent of the ISA across countries and industries in more detail, especially after 1990, when most of the changes have occurred. Table 3 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 two columns report 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 ISA is present in 11 out of 16 countries, 10 of which are very significant. Among the three country groups, the largest change is observed among emerging markets (2.19%), followed by large developed countries (0.95%).[11] Note that the level of the industrial structure difference between the U.S. and emerging markets is still markedly higher than that between the U.S. and the largest developed countries.

Panel B of Table 3 investigates industrial alignment by global sectors. 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 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%,

[11] The emerging market set consists of Greece, Korea, Mexico, and Portugal.

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 1990-2003 is only –0.50% and it is insignificant. Note however that while information technology shows the largest decrease in industrial alignment over time, its proportion in the industrial structure of the OECD countries in Panel A is much smaller than that of many other sectors.

The results in Figures 1 and Table 3 show a general tendency towards convergence in the industrial structures of the rest of the world and the U.S. with more evidence of alignment at the country level than at the industry level. Our findings imply that since 1990s, developed countries have become more diversified rather than specialized with respect to their industrial make-up. The increased alignment in the industrial composition, especially among large developed markets, must have implications on the dynamics of equity market returns and cross-country correlations at the country and industry levels. For instance, Roll (1992) suggests that industrial composition can explain substantial variation in national market stock returns. In the Appendix, we look at the impact of the alignment in industrial structure on country and industry correlations. There, we prove that the industrial structure alignment must increase country-level correlations more than industry-level correlations. Moreover, the changes in the industrial structure across countries must also be linked to financial and economic relations across countries.

3.3. Direct Link between Industrial Structure and Integration

The evolution of market capitalization across industries in response to ongoing economic and financial integration is likely to reflect their relative importance in the real economy as well. To examine the relation between ISA and world-wide integration more directly, we regress ISA on three variables, two of which, namely, trade share and market development have been extensively used in the literature as proxies for cross-market integration, (see Forbes and Chinn, 2004; and Bekaert and Harvey, 1995). Trade share is defined as the ratio of country's exports plus imports to its GDP; market development is the ratio of county's equity market capitalization to GDP. The third variable, market valuation, is a market integration proxy based on recent study by Bekaert et al. (2008) and it is the absolute difference between the price-to-earnings ratio in a given market and the US.[12] The macroeconomic data are obtained from the *International Financial Statistics*. One would expect a positive relation between ISA and all three integration proxies. Thus, we run the following panel regression of ISA on market integration variables as:

$$(2) \qquad ISA_t = \delta_0 + \delta_1 Trade\_Share_t + \delta_2 Market\_Development_t + \delta_3 Market\_Valuation_t + \varepsilon_t .$$

Table 4 reports the test results. It shows their point estimates, corresponding t-statistics, and adjusted R-squares. The ISA is in percent. The country fixed effects are included in the estimation but are not shown. The standard errors are based on the Newey-West correction with four lags. Columns 1, 2, and 3 show the results of regressing ISA on trade share, market development, and market valuation respectively, across all countries. The slope of the first variable is positive, consistent with the intuition, but insignificant, while that of the second and third variables are both positive and significant at the 1% level. In column 4, we regress ISA on all three integration proxies together. The result is similar: trade share remains insignificant while market development and market valuation stay positive and highly significant.

In the next three columns of Table 4, we split our sample into sub-samples of large developed, smaller developed, and emerging markets. We observe now that in statistical terms ISA has the most positive relation to two conventional economic and financial integration proxies (trade share and market development) among large developed markets. The trade share

[12] Our market valuation proxy is not exactly the same as in Bekaert et al. (2008). Their measure is based on the PE ratio differential between each country and the world within each industry and the country differential is computed as the aggregate of absolute differences at the industry level.

coefficient has also become positive and significant, at the 1% level. The market development coefficient is again positive and significant as for the overall sample. The market valuation variable is insignificant. Among small developed markets, we find an expected sign and significant relation between ISA and trade share and market valuation. In this case however, market development is insignificant. Finally, consistent with intuition, emerging countries show more signs of integration with the US via financial markets than economic real sector. The slopes on market development and market valuation in column 7 of the table are positive and highly significant, while trade share is negative and significant.

Thus, Table 4 shows that overall large developed markets exhibit more consistency between integration proxies and industrial structure than the other two country groups. This implies that because of ongoing integration processes they become more aligned with the U.S., i.e., more diversified. Our results are in line with Krugman and Venables (1995), Frankel and Rose (1998), Puga (1999), and Beine and Coulombe (2004) who argue that deep integration may lead to industrial diversification.[13]

4. Conditional Methodology

To examine the changes in cross-country equity return correlations as well as changes in output correlations we use a conditional framework. We assume that means, variances and covariances of stock returns and industrial production growth are time-varying. There are several important advantages of using conditional approach for the goals of this paper. First, as Forbes and Rigobon (2002) illustrate, many statistical techniques (e.g., moving window approach) create a bias in correlations when volatilities go up. Therefore, unconditional approaches are problematic when one needs to track changes in correlation over time.

[13] For instance, Beine and Coulombe (2004) support the existence of a positive long-run relationship between trade integration and industrial diversification for such closely linked countries as the U.S. and Canada. Importantly, their result holds for all sectors as well as for the manufacturing sector alone.

Conditional estimation techniques, such as GARCH are immune to that problem. Second, the conditional setting allows us to obtain correlation estimates making the full use of our data sample, which is somewhat limited for some markets along the time dimension. Third, we can apply a similar procedure 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 compare directly our results across both estimations.

We investigate the issues from the U.S. perspective and thus use U.S. country data as our base asset. 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,

$$r_{i,t} = E\left[r_{i,t} \mid \mathbf{Z}_{t-1}\right] + e_{i,t} = \mu_i + \mathbf{b}_i \mathbf{Z}_{t-1} + e_{i,t}, \tag{3}$$

where $r_{i,t}$ is the equity return on the *i*-th country, 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 return predictability (see Ferson et al. 2003; and the references therein), 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 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:

$$IP_{i,t} = \psi_i + b_{1i} IP_{i,t-1} + b_{2i} IP_{i,t-2} + e_{i,t}, \tag{4}$$

where $IP_{i,t}$ is the aggregate industrial production growth at time *t*, ψ_i is the unconditional average production growth, and e_i is a disturbance term. Thus, both the equity return and industrial production growth are modeled similarly as functions of two lagged information variables.

We use equation (2) or equation (3) to estimate a series of bivariate systems, where the first equation describes the dynamics of the foreign time series (stock returns or industrial production growth), while the second equation corresponds to the U.S. time series (the U.S. equity market portfolio or the U.S. industrial production growth).[14] In both of these systems,

$$e_t' = \left[e_{i,t}, e_{b,t}\right] \sim N\left(0, H_t\right), \tag{5}$$

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 et al. (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,

$$H_t = C'C + A'e_{t-1}e'_{t-1}A + B'H_{t-1}B + G'\eta_{t-1}\eta'_{t-1}G + D * t, \tag{6}$$

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 scalar, 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.

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.[15] We modify the covariance parameterization to test for a structural

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[14] Bivariate GARCH (1,1) models have been widely used in international asset pricing literature. For instance, Chan et al. (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.

[15] 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.

change in the correlation structure of the series. While the inclusion of a trend in the GARCH estimation does not lead to qualitatively different results from the estimation that does not use this component (see Section 5), it provides a framework for the statistical interpretation of the results. Our approach is similar to the correlation tests on equity data of Longin and Solnik (1995) where the constant conditional correlation model is modified with the introduction of a time trend. Since we are interested in the dynamics of the correlations of different data, the trend component allows us to directly test for the existence of trending behavior and at the same time meaningfully compare our results across estimations.[16]

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

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

We obtain the parameter vector Θ using 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:

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

[16] 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. They 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. However, there is no indication as to the predictive variables that would be common to both the equity

where r_b and r_i correspond to the returns on the base (U.S.) time series relative to which the correlations are computed and the foreign (non-U.S.) asset, respectively, while σ_b and σ_i are their respective conditional standard deviations.[17] We compute the average of the conditional correlations for industrial production growth in the same way.

5. Empirical Results

5.1. Test Results for Country-level Series

Figure 2 shows the time dynamics of two average pairwise country-level conditional correlation series between the U.S. and other 16 OECD countries. The first series is the correlation based on excess returns on countries' equity indexes. The second is based on the countries' aggregate industrial production growth rates. The plot shows that equity return correlations at the country have markedly increased and this increase has accelerated in the beginning of 1990's.[18] There is also an increase in the average aggregate production growth correlation although this change is not as drastic as for the equity return data.[19]

To attest to the statistical significance of our findings, Table 5 shows the average point estimates of the trend coefficients in cross-correlations of the U.S. equity market index returns or industrial production growth with country-level equity returns and industrial production

returns and economic series. Therefore, for the consistency of our methodology and inference across the estimation of the two datasets, we use a purely statistical model.

[17] 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.

[18] Our overall evidence of increasing equity return correlations is consistent with Longin and Solnik (1995) and Goetzmann et al. (2005). It is also consistent with Bekaert et al. (2006) who find an upward correlation trend only in European markets since most of the countries in our sample are from Europe.

[19] Our results do not necessarily contradict those of Heathcote and Perri (2004). They find that the output correlation between other developed countries and the U.S. has declined from the 1972-1985 to the 1986-2000 period with the largest drop (not surprisingly) observed between Japan and the U.S. However, their findings are not comparable to ours, since our comparison of real output correlations is limited to the post 1986 sample only. Further, for Canada, the most integrated country with the U.S., they also document an increase not only in output but also in consumption, investment, and employment correlations.

growth for 16 OECD countries, respectively. 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.

Panel A of Table 5 shows that all 16 trend coefficients of equity return correlations are positive and half of them are significant at the 10 per cent level or smaller. The largest significant gains in the correlation with the U.S. equity market are observed for emerging markets (due to the relatively low base-level correlation early in the sample). Similar to equity return correlations, there is more statistical evidence for upward trends in aggregate industrial production growth correlations, as indicated by Panel B. Across all 16 countries, there are five negative but insignificant trend coefficients, while the number of positive trend coefficients is 11, out of which 3 are significant.[20]

In Table 6 we present the residual diagnostics summary from the estimation of country-level equity market return and industrial production growth correlations.[21] Panel A shows that for equity returns there is no evidence of asymmetry, autocorrelation in the residuals (except for Finland) 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. Panel B shows that for industrial production growth there is still evidence of autocorrelation but it is generally much weaker than that for the corresponding raw data in Table 2. While many residual series are not normal, the extent of this non-normality is not as overwhelming as in the original production growth data.

[20] Following Dumas et al. (2003), we also checked the validity of industrial production as a proxy for output. We use quarterly GDP growth data for our 16 OECD countries and calculate their bivariate correlations with the U.S. GDP growth. Similar to the correlations for aggregate industrial production, we observe an increase in the average GDP-based correlations over time.

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

Similar behavior of country-level correlations for equity returns and industrial production growth over time raises the question of whether there is also a cross-sectional correspondence between these two correlation series. We address this issue in Figure 3. It depicts the relation between countries' equity return and aggregate industrial production growth correlations with the U.S. The sample size of country pair correlations is increased two-fold (from 16 to 32 observations) by splitting two sub-periods of the sample: 1986-1991 and 1998-2003. Each observation for each country is the average of conditional correlations with the U.S. over the given sub-sample period. We also removed the trend component from all estimations. We can see a positive relation between output growth and equity return correlations. This relation is also statistically significant at the 10% level. Thus, the higher is the correlation of a country's aggregate output growth with that of the U.S., the higher is also the correlation of its equity market returns with the equity market of the U.S.

5.2. Test Results for Industry-level Series

Given that shifts in the industrial structure are likely to play a role in the relative importance of different industries in a country's economy and financial market, we also investigate the dynamics of conditional correlations at the disaggregated level. We perform the same estimation described in Section 3 and generate correlations for the U.S. country index returns with industry level returns and for the aggregate U.S. industrial production growth with disaggregated output data of the 16 other OECD countries. While there is some evidence in the literature of increased return correlations at the country level, there is no systematic evidence for similar increases in correlations at the industry level.

Figure 4 shows the average pairwise correlations for equity returns and industrial production growth at the industry (disaggregated) level. The average industry-level correlations of returns have increased over the sample period. However, this increase is not as dramatic as for country-level correlations in Figure 1. As for the average disaggregated industrial production growth correlation, it remains at about 0.1 level over the entire sample period.

The statistical results on trend coefficients across all pairwise estimates of industry-level correlations are reported in Table 7. In Panel A, we find that correlations of equity returns at the industry level, unlike those at the country-level, sometimes exhibit negative trends, although their proportion is very small. There are 40 industry-level correlation series with significantly positive trends. Note that their proportion (40 out of 118) is smaller than the proportion of correlations with positive trends at the country level (8 out of 16). This again implies that cross-market correlations at the country level have increased more than at the industry level.

Panel B of Table 7 shows trend coefficients for the disaggregated industrial production correlations. Across all countries, there are 62 negative trends, out of which 9 are significant, while the number of positive trends 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, unlike Panel A, in Panel B we observe an equal (random) distribution of negative and positive trends across countries. Based on this, we can say that, similar to equity return correlations, there is statistical evidence that cross-market output correlations have increased more at the aggregate level than the disaggregated level.

Table 8 contains the diagnostics of the residuals similar to that in Table 6 but for disaggregated data. Panel A shows that for industry-level equity returns there is no evidence of asymmetry, autocorrelation in the residuals or squared residuals. The non-normality is still present but it is much weaker than in the raw data. Panel B shows the diagnostics for industrial output. The evidence is similar to what we discussed for the aggregate level estimations, with a general reduction in autocorrelations and non-normality. [22]

[22] The sample of correlations includes 130 series instead of 132 for equity returns and 128 instead of 133 for industrial production growth. The model generates few series with a very persistent variance. For seven equity return series, this feature was corrected through the estimation of a more parsimonious GARCH model without asymmetry. For 15 industrial production series, we address this issue by estimating a more parsimonious model with an AR(1) or a constant for the mean. A few series still showed a persistent variance even based on the

What contributes to the observed phenomena of larger increases in correlations at the aggregate level than disaggregate, both in the financial sector and the real economy? The most convincing argument for the increase in correlation at the country return or aggregate production growth level is the ongoing economic integration process across countries, especially developed economies. At the industry return or disaggregated production growth 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 et al. (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. Rajan and Zingales (1998) find that different sectors in countries with well functioning financial markets develop at a different pace. The macroeconomic literature offers additional insights on these processes. Backus et al. (1992) suggest that in open economies additional sources of shocks, such as industry-related, may be important for output fluctuations. Barth and Ramey (2001), and Dedola and Lippi (2005) document the heterogeneity of monetary policy effects across industries both in the U.S. and in some OECD countries using disaggregated industrial production data.

Thus, if government policies, either economic or financial, have heterogeneous effects on the sectors, cross-country convergence may show up more at the aggregate level due to policy coordination and not so much at the disaggregated level.[23] The alignment in the industrial structure across countries has an important impact on this process. It certainly drives up the country level correlations (both financial and economic), yet it may not equally affect the correlations at the industry level. We also show analytically in the Appendix that the increased alignment of industrial structure between countries, *ceteris paribus*, leads to larger

parsimonious models, and so they were excluded to preclude any biases in the average correlations. In all cases these series start in the 1990's, so this nonstationarity could be due to the short observation period.

[23] For instance, Baele (2005) finds an increase in the market spillover intensity among European countries in the 1990s.

correlation increases for returns at the market level than at the industry level.[24] Therefore, even a perfect alignment in the industrial structure of two fully integrated countries does not eliminate a heterogeneous impact of common country shocks on different industries. Our findings seem to corroborate this result.

5.3. Changes in Industrial Structure and Cross-Market Correlations

The similarity in the dynamics at the country level for equity market return correlations on one side and industrial production growth correlations on the other, suggests the existence of commonality in these relations. Hence, we want to know whether there is any relation between changes in industrial alignment and changes in cross-market correlations based on equity returns or real output.

Figure 5 illustrates the link between changes in correlations of equity returns and ISA. For each country, both series are equally-weighted across industries. As argued by Roll (1992), we expect that countries that experienced increased industrial alignment will display larger increases in return correlations. Plot A remarkably shows that this is indeed the case among 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.

Figure 6 illustrates the link between changes in correlations of industrial production growth and ISA. As with equity return correlations, for each country, both series are equally-weighted across disaggregated output. Based on the findings in Frankel and Rose (1998) and Dumas et al. (2003), we now expect that countries that experienced increased industrial alignment will display larger increases in output correlations. Plot A again shows that this is the

[24] Our findings 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. In an unreported estimation of the volatility dynamics of equity returns at the country and industry levels, we find that the difference between the two series is somewhat smaller in the beginning of the sample period than at the end.

case for large developed markets. However, as with equity return correlations, we find no relation for small developed or emerging markets in Plot B.

Thus, our results show that the increase in the industrial structure alignment in the 1990's has its reflection on both financial and economic linkages across countries. These findings are particularly strong among large developed countries.

6. Implications for International Portfolio Diversification

Our analysis based on equally-weighted averages of conditional correlations provides additional insights for the relative benefits of competing global portfolio allocation strategies. Evidence presented in DeMiguel et al. (2007) shows that naïve (1/N) diversification strategies perform better than those resulting from model-based optimization. This further justifies the use of equally-weighted averages in our analysis of both financial and economic time-series.

The first observation from Figures 2 and 4 is that the spread between country and industry-level equity return correlations has increased over time, implying that for a U.S. investor the *relative* benefits of industry diversification have increased over time vis-à-vis country diversification. This result does not contradict the conclusions of some of the best-known studies that report the importance of country over industry components in stock returns (e.g., see Heston and Rouwenhorst, 1994; Griffin and Karolyi, 1998). We make no claims as to the *absolute* benefits of diversifying across countries versus industries, that is, we are not inferring that industry diversification completely dominates country diversification.

The second observation from Figures 2 and 4 is that the spread between aggregate and disaggregated output correlations has also increased over time. If the correlation spreads in equity returns and industrial production growth have synchronous changes in their dynamics, then the increase in the *relative* benefits of industry diversification will have support in the real economy. We investigate this issue by testing for common deterministic trends in the two correlation spreads series using the methodology of Vogelsang and Franses (2005). We use the heteroskedasticity and autocorrelation consistent (HAC) estimator with the Bartlett kernel (see Newey and West, 1987) with two variations for the bandwidth. [25]

Table 9 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 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.

Thus, our results show that the increase in the industrial structure alignment in the 1990's coincides with an increase in the relative importance of industry diversification strategies vis-à-vis geographic ones over the same sample period. It also has a similar impact on the correlation of aggregate output across countries relative to that of the disaggregated, industry-specific output, with stronger statistical support for our set of developed countries. This parallel is particularly intriguing as it seems to indicate that the increase in the relative

[25] 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.

importance of industry diversification strategies is likely to be a permanent rather than a transitory phenomenon.[26]

7. Robustness Issues

7.1. Services and Non-services Sectors

One of the issues with the observed changes in the average industrial structure over time is that the alignment could be concentrated only in the services sector, since this sector has recently taken the leading economic role in all developed countries. To address this concern, we apply the abovementioned approach and re-compute our time-series measure of ISA separately for service and non-service sectors. Services sector consists of four industries: cyclical services, financials, information technology, and non-cyclical services.

Figure 7 presents the result. We show the dynamics of misalignment measure for both all service industries as well as for services excluding information technology. The most prominent feature of the service sector behavior is the spike in the misalignment in the late 1990's. Clearly, this spike is driven by the telecom and internet phenomenon, which implies that industry-specific bubbles lead to divergence rather than convergence in industrial structures across countries. When we exclude the information technology sector, the spike is much smaller but still present since the non-cyclical service sector includes telecom firms. The increase in the alignment of industrial structures of OECD countries with that of the U.S. in the 1990's is present across both service (excluding information technology) and non-service sectors, although more steadily among service industries. This result is not inconsistent with Krugman (1991) or Imbs and Wacziarg (2003). As developed countries move their activities

[26] Our conclusion is different from Baca et al. (2000) and Cavaglia et al. (2000). In these papers, the increase in the importance of industry factors is limited to a two-year period from 1997 to 1999. Brooks and Del Negro (2004) attribute this increase to the IT-bubble. However, Baele and Inghelbrecht (2007) report that geographical and industry diversification now give approximately the same diversification benefits, especially in Europe.

primarily towards service industries, one could indeed expect more re-alignment in industrial structure among those countries in the service sector.

Generally similar conditional correlations and alignment trends across service and non-service sectors of the economy should not come as a big surprise. Due to the reorganization of production across sectors in the economy and to rapid technological changes, the actual distinction between services and manufacturing sectors may in many cases be quite complicated (see Riet and Roma, 2006).

7.2. Bivariate GARCH(1,1) Estimation with no Trend Component

The inclusion of a trend in our estimation helps us assess some of our most important results in statistical terms. The existence of the trend in the conditional covariance equation also reinforces the effect of the trending behavior in the time-series when such behavior indeed takes place. Nevertheless, it may appear that having the trend in the GARCH estimation by itself may induce the results. To address this concern, we exclude the trend variable and we re-run our models (2) and (3).

Table 10 present the estimation results. The table shows the average conditional correlations of country- and industry-level equity returns and industrial production growth, as well as their corresponding spreads based on the GARCH(1,1) model without the trend component over the two equal time periods 1986-1994 and 1995-2003. It also shows the difference in all three measures between the two sub-periods.

First, the vast majority of average correlations, both for equity returns and industrial production growth are higher in the second period of the sample. Not surprisingly, the exceptions are aggregate and disaggregated industrial production growth among emerging countries. The latter also contributes to a lower average correlation of disaggregated industrial production growth with the U.S. across all countries in 1995-2003. Second, the change in the average correlations of both equity market returns and aggregate output growth are the highest among large developed markets, 0.095 and 0.020, respectively. This indicates the largest impact of industrial structure alignment on large developed countries. Third, all differences in correlation spreads from one period to another are positive. This implies that correlations with the U.S. are higher at the country level than industry level, both for equity returns and real output, corroborating with our earlier findings.

Thus, the inclusion of a trend in the GARCH estimation does not lead to qualitatively different results from the estimation that does not use this component. It simply highlights any existing trending behavior in the time series as well as provides a framework for the statistical interpretation of the results.

8. Conclusions

Our paper contributes to the ongoing debate about the impact of market integration on the financial and industrial structure across countries. Using data from the U.S. and 16 other OECD countries over the 1976-2003 period, we document a significant increase in the industrial structure alignment between the U.S. and other countries. This process has substantially accelerated in the post-1990 period.

Changes in the industrial structure across countries impact global linkages. Indeed, we find that the average conditional correlations of equity returns at the country level have increased starting around 1990. Combined with our results on industrial structure alignment, these findings confirm Roll's (1992) argument that industrial structure matters in explaining the dynamics of equity correlations. Most interestingly, our results on the importance of shift in industrial make-up are not limited to the financial side of the global economy. We show that the behavior of equity return correlations is mirrored on the real side where we also observe an increase in the average correlations of aggregate production growth rates, especially among large developed economies. We find instead that correlations among equity and industrial production at the disaggregated level have not increased by a comparable magnitude.

We explain our results by increasingly correlated shocks across countries at the equity market and aggregate output level resulting from the ongoing process of financial and economic integration. On the other hand, these policies are likely to have a heterogeneous impact at the disaggregated level that can explain the smaller increase in correlation.

Finally, our findings provide implication for global diversification strategies. Since the industrial make-up of developed countries is increasingly more similar to that of the U.S., the benefits of diversifying across industries have increased *relative* to country diversification for U.S. investors. Given the results on the real economy side, this is likely to be permanent.

Appendix

This appendix proves that an alignment in industrial structure between two countries has a different impact on country versus industry level correlations. Consider two fully integrated countries, each of which consists of the same two industries. Suppose that at time t = 1, these countries have different industrial structures and therefore their markets are not perfectly correlated. At time t = 1, let the country level correlation be equal to the industry level correlation, which is the equally-weighted average of correlations between country 1 and the two industries of country 2, namely:

$$\rho^C = \rho^I = \frac{1}{2}\left(\rho_{12}^1 + \rho_{12}^2\right) < 1,$$

where subscripts denote countries and superscripts denote industries. Here, country 1 is the base country (e.g., the U.S.).

We assume that the industrial structure of country 1 remains constant, so that country 2 aligns its industrial structure over time to that of country 1. Also, assume that the proportion of market capitalization of industry 1 in country 1's total market capitalization is w_1^1. This implies that the return on equity market 1 is the value-weighted average of returns on its constituent industries, that is,

$$R_1 = w_1^1 R_1^1 + \left(1 - w_1^1\right) R_1^2 ,$$

and the total variance of market 1 returns is

$$\left(\sigma_1\right)^2 = \left(w_1^1 \sigma_1^1\right)^2 + \left(\left(1 - w_1^1\right)\sigma_1^2\right)^2 + 2 w_1^1 \left(1 - w_1^1\right) \rho_{11}^{12} \sigma_1^1 \sigma_1^2 ,$$

where σ_1^1 and σ_1^2 are the volatilities of industry 1 and industry 2 returns, respectively, in country 1, while ρ_{11}^{12} is the correlation between industries 1 and 2 in country 1. Then:

$$\begin{aligned}
\rho^I &= \frac{1}{2}\left(\frac{Cov\left(R_1, R_2^1\right)}{\sigma_1 \sigma_2^1} + \frac{Cov\left(R_1, R_2^2\right)}{\sigma_1 \sigma_2^2} \right) = \\
&= \frac{1}{2}\left(\frac{w_1^1 Cov\left(R_1^1, R_2^1\right) + \left(1 - w_1^1\right) Cov\left(R_1^2, R_2^1\right)}{\sigma_1 \sigma_2^1} + \frac{w_1^1 Cov\left(R_1^1, R_2^2\right) + \left(1 - w_1^1\right) Cov\left(R_1^2, R_2^2\right)}{\sigma_1 \sigma_2^2} \right) \\
&= \frac{1}{2}\left(\frac{w_1^1 \sigma_1^1 \sigma_2^1 \sigma_2^2 \rho_{12}^{11} + \left(1 - w_1^1\right)\sigma_1^2 \sigma_2^1 \sigma_2^2 \rho_{12}^{21} + w_1^1 \sigma_1^1 \sigma_2^1 \sigma_2^2 \rho_{12}^{12} + \left(1 - w_1^1\right)\sigma_1^2 \sigma_2^1 \sigma_2^2 \rho_{12}^{22}}{\sigma_1 \sigma_2^1 \sigma_2^2} \right) \\
&= \frac{1}{2\sigma_1}\left(w_1^1 \sigma_1^1 \left(\rho_{12}^{11} + \rho_{12}^{12}\right) + \left(1 - w_1^1\right)\sigma_1^2 \left(\rho_{12}^{21} + \rho_{12}^{22}\right)\right).
\end{aligned}$$

Suppose, at time $t = 2$, the two countries achieve perfect alignment in their industrial structures, that is, $w_1^1 = w_2^1$ and $w_1^2 = w_2^2$. Since they are also perfectly integrated, $R_1^1 = R_2^1$ and $R_1^2 = R_2^2$. Accordingly, $R_1 = R_2 = R$, $\sigma_1 = \sigma_2 = \sigma$ and, so, $\breve{\rho}^C = 1$. (The ark on the correlation coefficient denotes the case with fully aligned industrial structures). On the other hand, $\breve{\rho}^I < 1$, because different industries within or across countries cannot be perfectly correlated due to different industry-specific shocks. Indeed, under perfect industrial structure alignment, the same industries in both countries will be perfectly correlated, i.e., $\breve{\rho}_{12}^{11} = \breve{\rho}_{12}^{22} = 1$, and all cross-industry correlations must be equal to each other, i.e., $\breve{\rho}_{11}^{12} = \breve{\rho}_{12}^{12} = \breve{\rho}_{12}^{21} = \breve{\rho}^{xi} < 1$, where superscript *xi* stands for cross-industry correlation. Therefore,

$$\breve{\rho}^I = \frac{\left(1 + \breve{\rho}^{xi}\right)}{2\sigma_1}\left(w_1^1 \sigma_1^1 + \left(1 - w_1^1\right)\sigma_1^2 \right).$$

Note that $\breve{\rho}^{I}$ is a positive linear function of $\breve{\rho}^{xi}$ for any given values of w_1^1, σ_1^1, and σ_1^2. If $\breve{\rho}^{xi} = -1$, then $\breve{\rho}^{I} = 0$. If $\breve{\rho}^{xi} = 1$, then $\breve{\rho}^{I} = 1$, since in this case one can write:

$$
\begin{aligned}
\left(\breve{\rho}^{I}\right)^2 &= \frac{\left(1+\breve{\rho}^{xi}\right)^2}{4\left(\sigma_1\right)^2}\left(w_1^1\sigma_1^1 + \left(1-w_1^1\right)\sigma_1^2\right)^2 \\
&= \frac{4}{4\left(\sigma_1\right)^2}\left(\left(w_1^1\sigma_1^1\right)^2 + \left(\left(1-w_1^1\right)\sigma_1^2\right)^2 + 2w_1^1\left(1-w_1^1\right)\sigma_1^1\sigma_1^2\right) \\
&= \frac{1}{\left(\sigma_1\right)^2}\left(\sigma_1\right)^2 \\
&= 1.
\end{aligned}
$$

Therefore, with the two extreme values known, we can state that for any $-1 < \breve{\rho}^{xi} < 1$, $0 < \breve{\rho}^{I} < 1$. This implies that at time t = 2, $\breve{\rho}^{C} = 1$ but $\breve{\rho}^{I} < 1$. Since at time t = 1, $\rho^{C} = \rho^{I} < 1$, the increase in the alignment of industrial structure between the two countries increases their country-level correlations more than industry-level correlations.

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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 UCC. 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 unconditional cross-correlations of country equity returns and number of different industries per country. The last two columns in Panel B show the average unconditional 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 UCC	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 UCC	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, as well as average unconditional cross-correlations, Ave UCC. 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 unconditional 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 unconditional 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 UCC	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 UCC	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 – 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 shows the alignment of industrial structure across countries while Panel B – across global industries.

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 4 – Industrial Structure Alignment and Market Integration

The table shows the estimation results from the regression of industrial structure alignment (in percent) on monthly measures of two country-specific integration proxies, trade share and market development. Trade share is defined as the ratio of country's exports plus imports to its GDP. Market development as the ratio of country's equity market capitalization to GDP. Market valuation is the absolute difference between price-to-earning ratio in a given country and the US. 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. The p-values are in parentheses. LD, SD, and EM stand for the largest developed, smaller developed, and emerging markets, respectively. The country fixed effects are included in the estimation but are not shown. The standard errors are based on the Newey-West correction with four lags. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	All	All	All	All	LD	SD	EM
Observations	3960	3960	3960	3960	1022	1559	748
Trade Share	1.190			-0.196	4.069 [a]	4.705 [a]	-15.072 [a]
	(0.334)			(0.530)	(0.001)	(0.000)	(0.000)
Market Development		0.131 [a]		0.110 [b]	0.076 [a]	-0.026	0.468 [a]
		(0.004)		(0.011)	(0.000)	(0.608)	(0.001)
Market Valuation			0.054 [a]	0.054 [a]	-0.012	0.038 [b]	0.064 [a]
			(0.000)	(0.000)	(0.252)	(0.015)	(0.000)

Table 5 – Tests on Country-level Correlation Trends

The table shows the average point estimates of the trend coefficients in cross-correlations of the U.S. equity market index returns or industrial production growth with country-level equity returns and industrial production growth for 16 OECD countries, respectively. 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).

Panel A: Equity returns correlations

		Negative trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
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

Panel B: Industrial production correlations

		Non-positive trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
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

Table 6 – Country-level Residual Diagnostics

The table shows the following 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 (Panel A) and industrial production growth (Panel B) for the 16 OECD countries. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: Equity returns correlations

	$LB(z)_{12}$	$LB(z^2)_{12}$	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: Industrial production growth correlations

	$LB(z)_{12}$	$LB(z^2)_{12}$	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

Table 7 – Tests on Industry-level Correlation Trends

The table shows the average point estimates of the trend coefficients in cross-correlations of the U.S. equity market index returns and industrial production growth with industry-level equity market returns and industrial production growth for 16 OECD countries. There are 130 series of equity return correlations and 128 series of industrial production growth correlations at the industry-level. 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).

Panel A: Equity returns correlations

		Negative trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
All countries	5.756	12	-1.257	1	118	5.374	40
	(0.307)		(0.608)			(0.285)	
Large Developed	5.309	3	-0.374	0	45	5.680	17
	(0.286)		(0.506)			(0.272)	
Small Developed	4.163	6	-2.062	1	46	4.958	15
	(0.322)		(0.612)			(0.284)	
Emerging	9.549	3	-0.530	0	27	9.963	8
	(0.315)		(0.704)			(0.315)	

Panel B: Industrial production growth correlations

		Non-positive trend			Positive trend		
	Ave	#<0	Ave<0	#*<0	#>0	Ave>0	#*>0
All countries	0.010	62	-0.361	9	66	0.354	6
	(0.478)		(0.467)			(0.480)	
Large Developed	-0.099	26	-0.275	6	18	0.185	3
	(0.439)		(0.428)			(0.424)	
Small Developed	0.120	24	-0.371	3	32	0.410	2
	(0.498)		(0.510)			(0.498)	
Emerging	-0.035	12	-0.530	0	16	0.436	1
	(0.499)		(0.468)			(0.506)	

Table 8 – Industry-level Residual Diagnostics

The table shows the following 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 for each industry group are shown for the equally weighted averages of local industry returns (Panel A) industry-level industrial production growth (Panel B). There are 336 equity returns observations from January 1976 to December 2003 and 168 industrial production growth observations from January 1986 to December 2003. All data are from Datastream. Superscripts a, b, and c denote statistical significance at the 1%, 5%, and 10% levels respectively.

Panel A: 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

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 9 – 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 (2005) 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.

	(1)	(2)	(3)	(4)	(5)	(6)
Bandwidth	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 10 – Average Correlations of Equity Returns and Industrial Production growth based on the GARCH(1,1) Model with no Trend

The table shows the average conditional correlations of country- and industry-level equity returns and industrial production growth, as well as their corresponding spreads based on the GARCH(1,1) model without the trend component over the two equal time periods 1986-1994 and 1995-2003. It also shows the difference in all three measures between the two sub-periods.

	1986-1994			1995-2003			Difference		
	Country	Industry	Spread	Country	Industry	Spread	Country	Industry	Spread
Equity returns:									
All countries	0.411	0.307	0.104	0.484	0.331	0.153	0.073	0.024	0.049
Large Developed	0.424	0.336	0.088	0.519	0.359	0.161	0.095	0.023	0.073
Small Developed	0.418	0.260	0.158	0.498	0.284	0.214	0.080	0.024	0.056
Emerging	0.358	0.271	0.095	0.416	0.309	0.107	0.058	0.038	0.012
Industrial production growth:									
All countries	0.104	0.061	0.044	0.112	-0.059	0.053	0.008	-0.120	0.009
Large Developed	0.146	0.072	0.074	0.166	0.074	0.092	0.020	0.002	0.019
Small Developed	0.079	0.068	0.011	0.085	0.071	0.013	0.006	0.003	0.002
Emerging	0.098	0.035	0.063	-0.092	-0.020	0.072	-0.190	-0.055	0.009

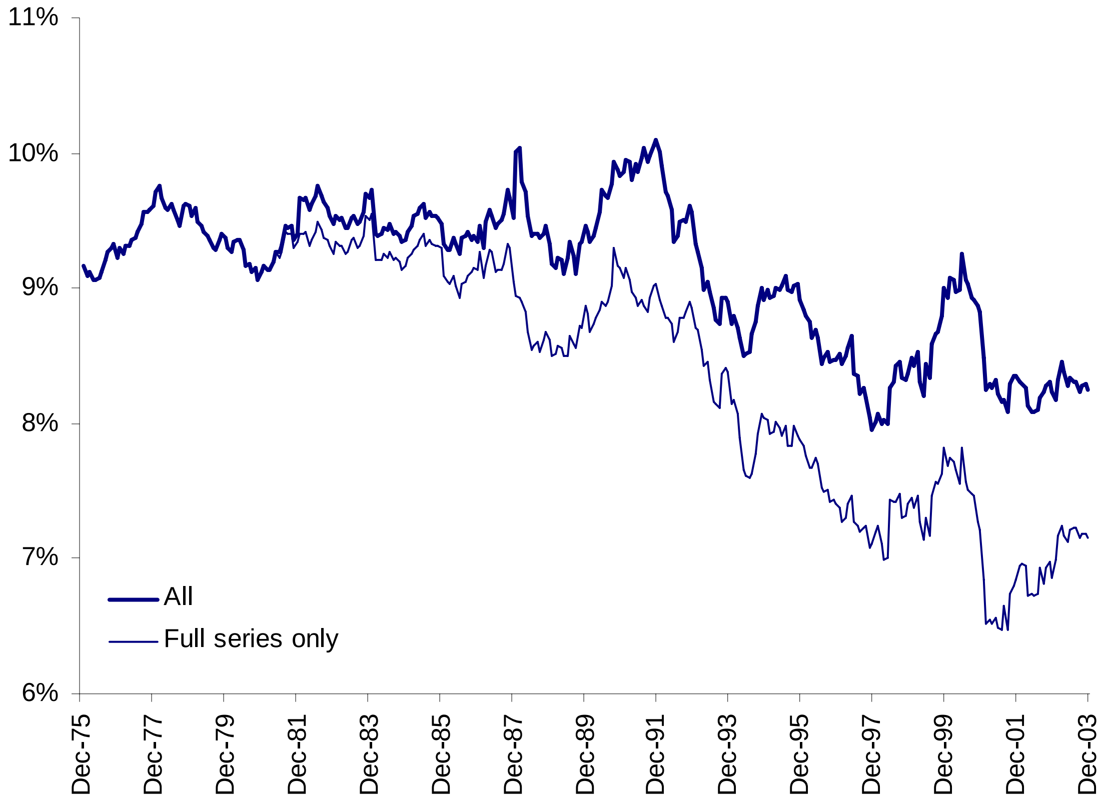


Figure 1. Industrial structure alignment

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 as well as based on only those series that existed during the entire sample period (66 in total).

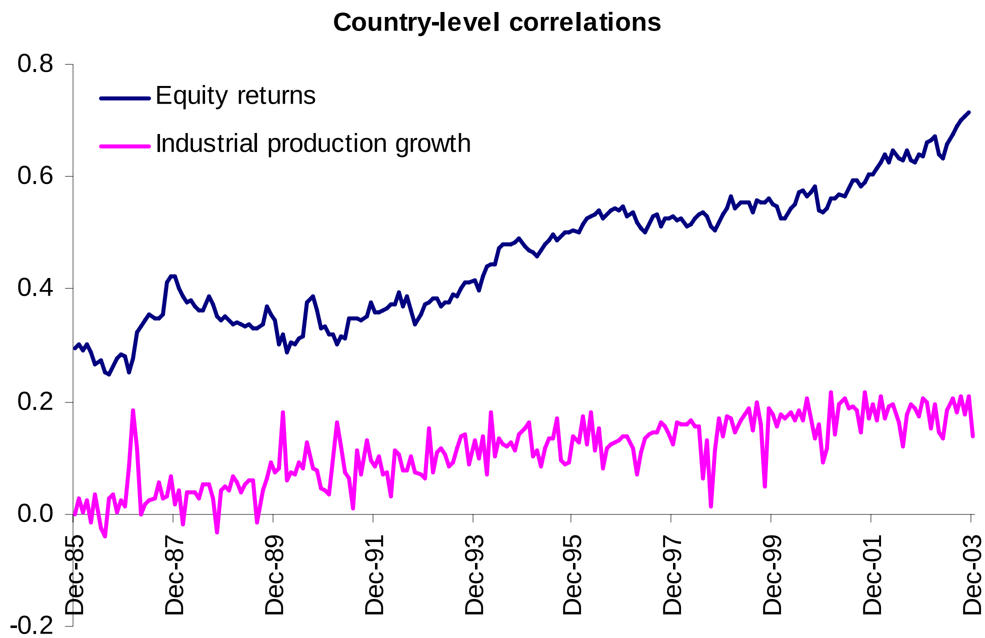


Figure 2. Average pairwise country-level conditional correlations

The figure depicts two average pairwise country-level conditional correlation series between the U.S. and other 16 OECD countries. The first series is the correlation based on excess returns on countries' equity indexes. The second is based on the countries' aggregate industrial production growth rates.

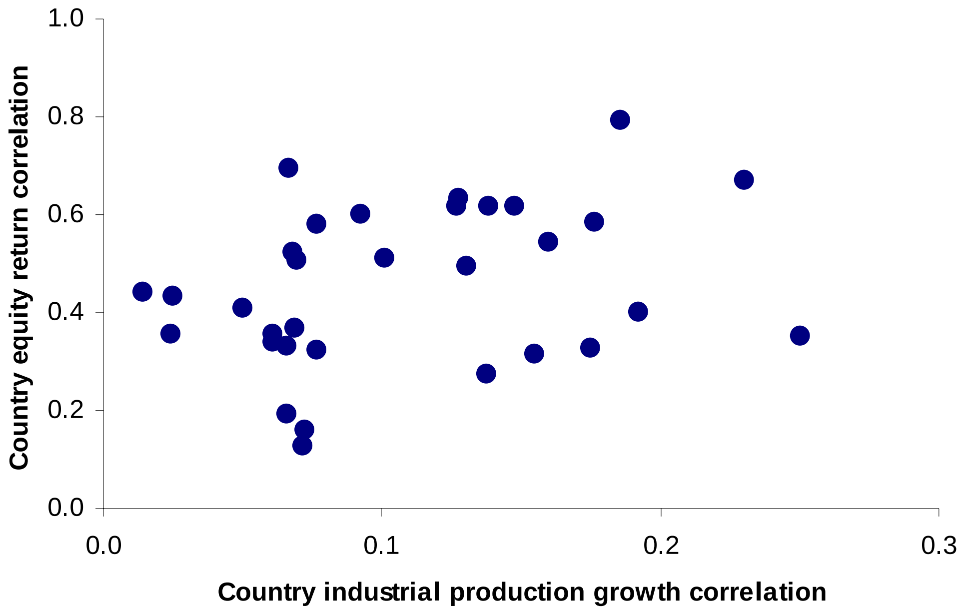


Figure 3. Relation between equity return and industrial production growth correlations

The figure depicts the relation at the country level between countries' equity return and industrial production growth correlations with the U.S. The sample size of country pair correlations is increased two-fold (from 16 to 32 observations) by using the two sub-periods of the sample: 1986-1991 and 1998-2003. The trend is removed in all estimations.

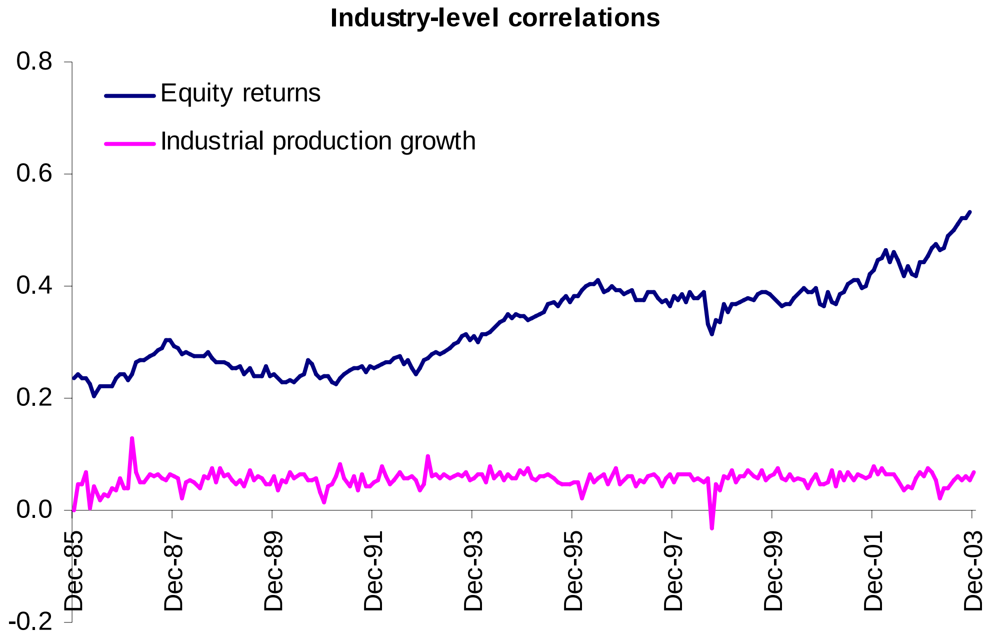
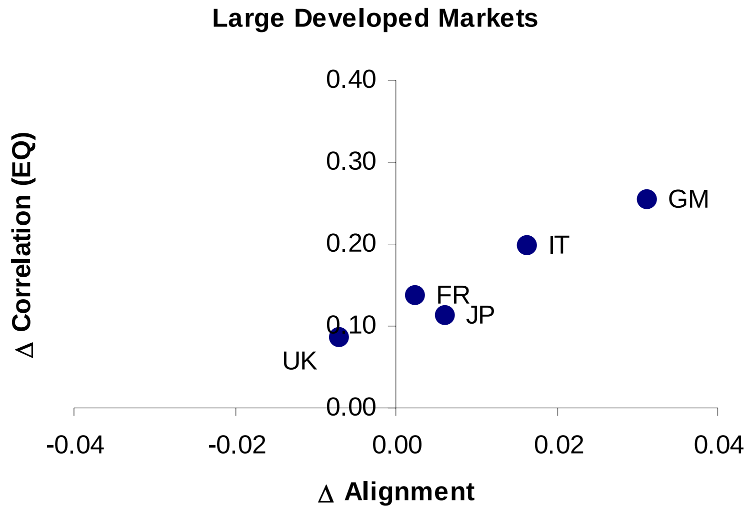
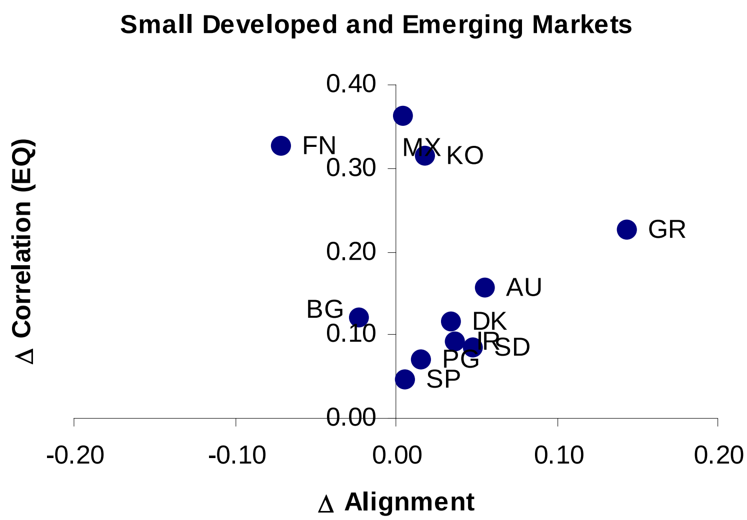


Figure 4. Average pairwise industry-level conditional correlations

The plot depicts two average pairwise industry-level conditional correlations between the U.S. and industries in other 16 OECD countries. The first series is the correlation based on excess returns on industries' equity indexes in each country. The second is based on the countries' disaggregated industrial production growth rates.



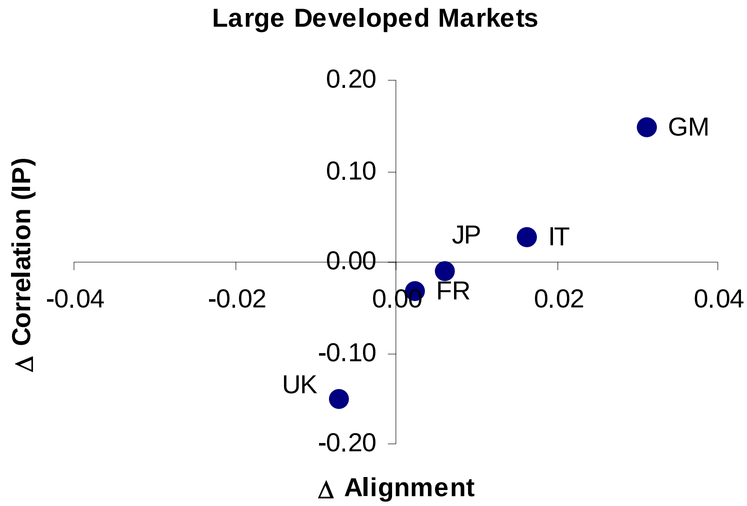
A



B

Figure 5. Changes in correlations of 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 1986-1991 to 1998-2003. For each country, both series are equally-weighted across industries. 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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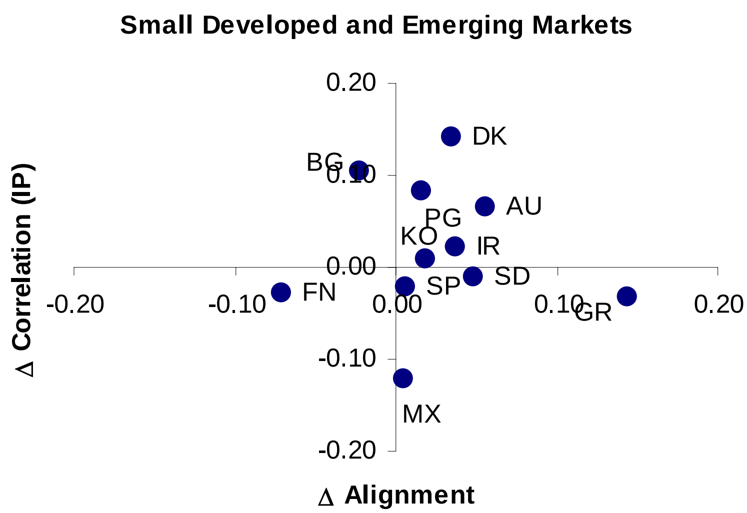

B

Figure 6. Changes in correlations of production growth and industrial structure alignment

The figure depicts the relation between the changes in the country-level industrial production growth correlations and changes in industrial structure alignment from 1986-1991 to 1998-2003. For each country, both series are equally-weighted across industries. 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.

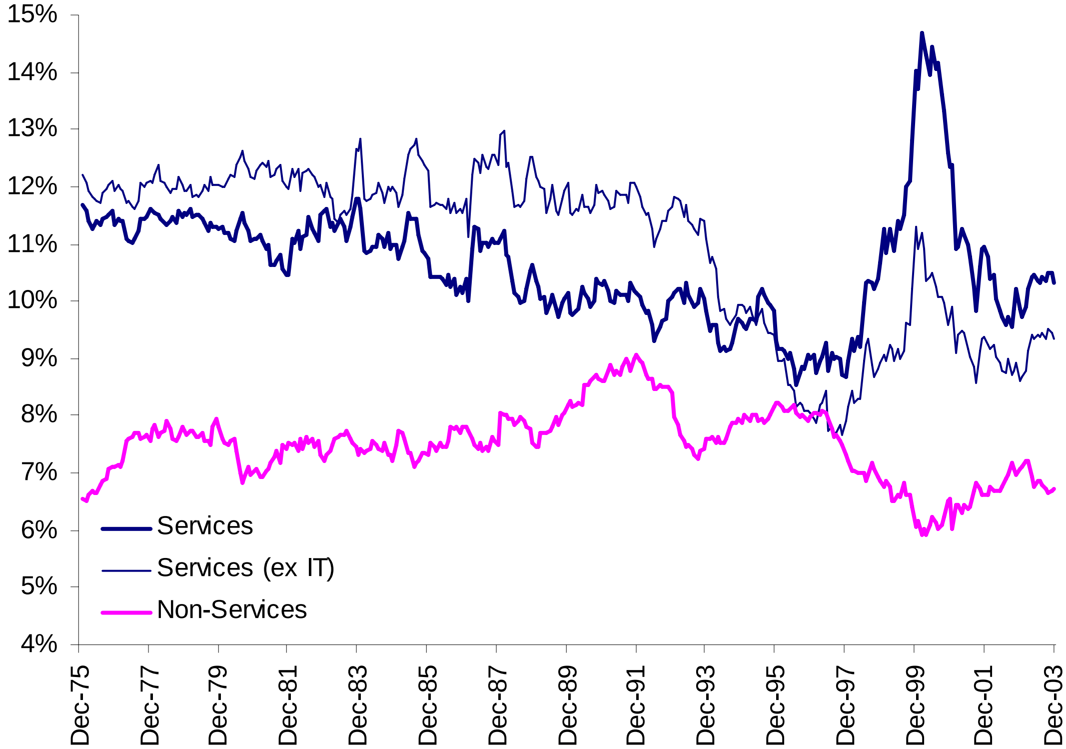

Figure 7. Industrial structure misalignment across services and non-services sectors.

The figure depicts the time variation in the industrial structure alignment between the U.S. and other countries across services and non-services industries. 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.