Stock Market Comovements and Industrial Structure

Pushan Dutt*
INSEAD

Ilian Mihov†
INSEAD

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Abstract

We use monthly stock market indices for 58 countries to construct pairwise correlations of returns and explain these correlations with risk-adjusted differences in the industrial structure across these countries. We find that countries with similar industries have stock markets that exhibit high correlation of returns. The results are robust to the inclusion of other regressors like differences in income per capita, stock market capitalizations, measures of institutions, as well as various fixed time, country and country-pair effects. Our results are consistent with models in which the impact of each industry-specific shock is proportional to the share of this industry in the overall industrial output of the country.

JEL Classification: G15, G11, O14

Keywords: International stock market correlations; industry structure; trade structure.

* INSEAD, 1 Ayer Rajah Avenue, Singapore 138676; Email: Pushan.Dutt@insead.edu, Ph: + 65 6799 5498
† INSEAD, 1 Ayer Rajah Avenue, Singapore 138676; Email: Ilian.Mihov@insead.edu, Ph: + 65 6799 5434

1 Introduction

Recent years have witnessed a rapid increase in comovements across stock markets. Figure 1 shows substantial variation in the average cross country correlations for 325 pairs of countries over the time period 1970-2006.[1] The average of all country-pair correlations of MSCI indices for 58 countries was in excess of 0.6 in 2006. One contributing factor is undoubtedly the slow and steady erosion of barriers to portfolio flows. More recently, some of the increase in correlation is likely related to the financial crisis in the US in 2008-2009.

A lot of academic attention has been devoted to relating the observed stock return co-movement to fundamentals.[2] A new strand of literature pointing out to the role of industrial composition in explaining cross-country correlations started with the seminal work of Roll (1992). After studying the role of industry factors in explaining the cross-country variation in returns across 24 mostly developed economies, Roll (1992) provides an analysis of stock market correlations and concludes "that a significant portion of the international structure of correlations among country returns ... is induced by the industrial compositions of the country indexes." Using country-specific industry weights, he constructs artificial returns for each country based on industry-weighted portfolios. The importance of industry factors is established by comparing the correlations of these artificial portfolios to the correlations of actual stock market returns. Standard statistical tools suggest that the match between constructed portfolios and actual indices is reasonably high, which leads Roll to conclude that industrial composition plays a significant role in explaining comovements across stock markets.

This conclusion has been challenged by Heston and Rouwenhorst (1994). By providing

[1] Computed using monthly returns over a 60 month rolling window. The country pair correlations range from -0.75 in the year 1989 for India and Japan to 0.98 in the year 2006 between Germany and Japan. To calculate the average correlations, we use only 26 countries for whom we have data for each year, over the period 1970-2006. This is to avoid composition effects.

[2] See Karolyi and Stulz (2003) for a survey.

a more detailed decomposition of returns into country-specific and industry-specific components, they show that industry effects have a negligible contribution to cross-country correlations. They state explicitly that "[i]n sharp contrast to the findings of Roll (1992), we conclude that industry composition cannot account for the low country correlations."

Recently, Carrieri, Errunza and Sarkissian (2007) have revisited this question by employing a different methodology and a different data set. They study the evolution of stock market correlations between 16 OECD economies and the US stock market as the industrial structure of these economies becomes more or less similar to the US structure. In a series of plots they show that countries that have become more similar to the US in their industrial composition, have also seen an increase in the correlation of their stock markets with the US stock market.

Thus far the literature has evaluated the importance of industrial similarity or industry shocks by using stock market data either to extract industry effects or to construct series for industrial similarity based on stock market capitalization. Our contribution to the literature is threefold: First, we directly use industry production data to establish industrial similarity. For any two pairs of countries we construct a measure based on the relative contribution of each industry to the value added in the country. This measure is a time-varying, country-pair-specific index of differences in production. Next, we examine within a rich econometric specification whether comovements between stock market returns are driven by similarities/differences in industrial structure as captured by this index. By using value added data at the industry-level to extract shocks, we get closer to the fundamental drivers of economic performance and we minimize the measurement error associated with non-fundamental drivers of stock market returns.

Second, our regression setup allows us to control for a large number of country-specific, pair-specific and time specific fixed effects in addition to including some important control variables like similarity in economic development. Indeed, the main criticism of Roll's work by Heston and Rouwenhorst (1994) is that Roll's paper does not control for or separate out country effects. We take this argument further by controlling not only for country effects, but also for country-pair as well as time fixed effects.

Finally, our study provides a non-trivial extension of the data set. While all of the papers in this area have focused on similarities among developed economies, we use data for 58 countries including 35 emerging markets. The time coverage in our data set is from 1970 to 2006. This extension of the data set is important not only from a purely robustness viewpoint. To see the need for a broader data set, consider the paper by Carrieri et al. (2007). They study only similarity of OECD economies with the US. While their conclusions about the dynamics of stock market comovements with the US are quite insightful, the paper has nothing to say about correlations among emerging markets, or even among other developed economies. In other words, in a setup studying only correlations with the US, we cannot distinguish between hypotheses like: countries that converge to the US have more correlated markets with the US because the US plays a special role in global financial markets vs. countries that have similar industrial structure– irrespective of their level of economic development – have high levels of stock markets correlation.[3]

As in the seminal paper by Roll (1992), we expect that countries that are similar in their industrial structure will exhibit higher degree of comovements. The intuition behind this is simple. Consider a pair of countries that are similarly specialized in the production of a set of goods. In such a setting, global sector specific shocks will lead to a movement of returns in both countries in the same direction and we should observe a high correlation in national stock market returns even if the stock markets are segmented. Furthermore, our measure of industrial similarity allows us to go deeper and account for realizations where country-pairs specialize in different sectors, but their stock returns still move together because *the covariance of shocks* in the sectors that they produce is high. Country-pairs that specialize in very different sectors and where the covariance of sectoral shocks is low or close to zero

[3] In an online appendix available at http://faculty.insead.edu/dutt/stockcorr we show correlations for various country-pairs.

will exhibit low comovements in stock returns.

To operationalize this insight we use the methodology developed by Koren and Tenreyro (2007) to calculate the variance-covariance matrix of global shocks at the sectoral level and construct a risk-adjusted (or volatility-weighted) differences in production structures. This variable is a summary measure that explicitly takes into account a) differences in production shares between pairs of countries; b) volatility of sectoral shocks and c) covariances between sectoral shocks. Across an array of specifications and for different country-pair sub samples, we find that pairs of countries with smaller risk-adjusted production structure differences tend to exhibit similar movements in stock market returns.

We start by showing that the *unconditional correlations* in stock returns depend negatively on difference in the structure of production. Next, we estimate two asset pricing models and use the residuals from these models to calculate *conditional correlations*. The first is the Fama-French model (Fama and French 1996, 1998) and the second is an international and regional CAPM model (Bekaert and Harvey 1995, 1997). Embedding the correlations in these asset pricing models allows us to control for comovements due to the style of the stocks involved (Fama-French), and for comovements that may be ascribed to variations in world and regional integration for different countries (international and regional CAPM). We show that conditional correlations are higher for country-pairs with similar risk-adjusted production structures. We show that all of the results documented in the paper are robust to controlling for a wide range of differences between country-pairs that may plausibly affect return correlations - these span differences in levels of development, in financial sector development, differences in political institutions, trade links between these countries, and geographic proximity. Moreover, this relationship is stronger in segmented as opposed to integrated markets.

The correlation of index returns and its changes over time have important ramifications for investors looking to diversify their portfolios. More importantly, it requires a clear understanding of the sources of gains from diversification. As the brief introduction to the literture shows, there is no consensus on the importance of industrial composition in explaining cross-country correlations. While some argue in favor of the importance of industry factors (Roll, 1992; Campa and Fernandes, 2006; Flavin, 2004) others maintain that the gains stem from the diversity of economic conditions underlying foreign capital markets due to differences in monetary and fiscal policies, movements in interest rates, budget deficits, and national growth rates (see Heston and Rouwenhorst 1994, 1995; Griffin and Karolyi, 1998; Serra, 2000). Many of the latter studies rely on the Heston and Rouwenhorst (1994) methodology of regressing country stock returns on industry and country dummies, and then examining the relative importance of these industry and country effects. This is a convenient methodology to capture the relative importance of the two factors under certain assumptions about the correlation structure of shocks. Technically, if we decompose stock returns into industry, country, and idiosyncratic shocks, nothing prevents these shocks from being correlated with one another.[4] Rather than using the dummy variable methodology, we quantify differences in production structures across countries and examine the role it plays, if any, in stock market comovements. Our approach will not be able to answer whether industry or country effects are prevalent, but it will help us understand how the industrial evolution across countries shapes cross-country stock market correlations. Second, industrial development also seems to be related closely to diversification across sectors (Imbs and Wacziarg, 2003), and the inherent riskiness of these sectors. So while countries differ in the industries that they produce in, it is important to also account for the idiosyncratic volatility of sectors and the comovements of the industrial sectors themselves.[5] Therefore, we adopt a different

[4]In the Heston and Rouwenhorst (1994) setup returns are regressed on country and industry dummies in cross-sectional monthly regressions. The shocks (or industry and country-specific returns) are obviously not the dummies but the coefficients on these dummies. There is no mechanical link that requires the time-varying industry and country coefficients to be orthogonal to each other.

[5]Imbs (2004) provides a similar approach combining trade, financial and specialization factors to tease out the key determinants of business cycles synchronicity. He does identify industrial similarity as an important factor, as we do, but his key dependent variable is business cycle correlations.

modeling framework which shows that returns of countries are more likely to move together if 1) they produce in the same sectors; 2) that this effect is magnified when they produce in similar sectors that have higher idiosyncratic volatility, that is sectors exposed to large and frequent shocks, and 3) when they produce in different sectors but the covariance of sectoral shocks is high.

The rest of the paper is organized as follows: section 2 develops our measure of risk-adjusted differences in production structure; section 3 provides a brief description of our data, the data sources and presents various summary statistics; section 4 presents regression results showing the relationship between risk-adjusted differences in industry structure and unconditional stock market correlations between pairs of countries; section 5 uses conditional correlations instead of unconditional ones; section 6 replicates the analyses for various sub-samples, and analyzes the effect of country-specific stock market liberalization; section 7 concludes.

2 A Risk Adjusted Measure of the Differences in Structure of Production

In this section, we show how stock return correlations depend on the structure of production and on a matrix of global sector specific shocks, that captures the inherent volatility and comovement properties of sectors. We draw on Koren and Tenreyro (2007) and di Giovanni and Levchenko (2008) to construct such a sector-level covariance matrix that is common across countries and years. We combine this covariance matrix of sectoral shocks with differences in production shares for each available country-pair and time period to construct a summary measure that we term the risk-adjusted difference in production structure.

When constructing this measure, we explicitly recognize that financial market liberalization and integration with the world market may make stock returns more correlated with world market factors in a multi-factor framework (Bekaert and Harvey, 2000). For instance, developed countries with similar industrial structures may simply be more integrated with world markets so that their comovements reflects this rather than any aspects of industrial structure. Therefore, we embed our estimation strategy in 1) a Fama-French model, and 2) an international and regional CAPM model. Assume that the excess stock return in country i at time τ (in months) $R_{i\tau}$ is written using either of these two models as

$$R_{i\tau} = \Phi^h_{i\tau}\left(\mathbf{M}\boldsymbol{\beta}\right) + e_{i\tau}$$

where Φ^h refers to the Fama-French model or the international and regional CAPM model.[6] Now assume that the residuals $e_{i\tau}$ can be written as a weighted average of sector-specific shocks $\epsilon_{k\tau}$ which is the global shock to sector k at time τ.

$$e_{i\tau} = \lambda \sum_{k=1}^{K} pshare^i_{k\tau}\epsilon_{k\tau}$$

Each of the K sectors receives a weight $pshare^i_{k\tau}$ which is the production share of sector k in country i at time τ. Since the global sector-specific shocks are based on value-added in each sector, we use λ as a parameter that relates value-added shocks to innovations in stock returns. Similarly, for country j in time τ we can write

$$e_{j\tau} = \lambda \sum_{k=1}^{K} pshare^j_{k\tau}\epsilon_{k\tau}$$

Subtracting we get

$$e_{i\tau} - e_{j\tau} = \lambda \sum_{k=1}^{K}\left(pshare^i_{k\tau} - pshare^j_{k\tau}\right)\epsilon_{k\tau}$$

We can calculate then the variance of this difference year-by-year (indexed by t) as:

$$\sigma^2_{i,t} + \sigma^2_{j,t} - 2cov_t\left(e_i, e_j\right) = \lambda^2 \mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}$$

This expression shows the link between annual volatility of unexpected stock market returns in any pair of countries and the covariance between these returns as a function of λ, the (K

[6] See section 6 for more details on the two factor models.

x 1) vector of differences in production shares $\left(pshare^i_{k,t} - pshare^j_{k,t}\right)$ denoted by $\mathbf{a}_{ij,t}$ and the variance-covariance matrix of global shocks to the K sectors denoted by Ω. Since our value-added data is annual, we will not be able to calculate annual values for the variance-covariance matrix of shocks. We will use the full sample to obtain a time-invariant estimate for Ω. The conditional correlation of stock returns in each year t is given by

$$\rho_{ij,t} = \frac{\sigma^2_{i,t} + \sigma^2_{j,t}}{2\sigma_{i,t}\sigma_{j,t}} - \frac{\lambda^2}{2}\frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}} \tag{1}$$

The last term $\frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$ is our measure of risk-adjusted differences in the structure of production. It combines volatility of different sectors (diagonal elements of Ω), covariances across sectors (off-diagonal elements) and industrial similarity ($\mathbf{a}_{ij,t}$). Country-pairs with high values of $\frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$ are countries that have either very different production structure, or they have small differences but in very volatile industries, or they specialize in industries with uncorrelated or negatively correlated shocks. Countries with high values of this measure will exhibit lower comovements in stock market returns.

3 Data, Variables and Specification

3.1 Stock Returns

Our dependent variable is the correlation between returns on country stock indices. Our sample of national equity markets includes data for both developed markets, as compiled by Morgan Stanley Capital International (MSCI), and emerging markets from S&P's Emerging Market Database (EMDB). We use monthly data from MSCI for stock market indices, over the period 1970-2006. We complement this data with monthly stock indices from EMDB that covers 35 emerging country markets with data beginning in 1975. Next, we calculate monthly returns and subtract the 1-year risk free T-bill rate for the US to obtain excess returns. We used this monthly excess return to calculate pairwise unconditional correlations over the 12 months of each year.[7]

3.2 Risk-Adjusted Differences in Production Structure

We construct our measure of risk-adjusted differences in production structure in two steps. First, we calculate a variable measuring only differences in the industrial structure. This measure is not influenced by the volatility of industry-specific shocks or by the correlation of these shocks across industries. To construct this measure, we use industry-level panel data on production. The data on industry structure is from the UNIDO database which provides annual data on production, value-added, employment, and number of firms for 28 manufacturing sectors (3 digit ISIC codes are reported) for 183 countries over the time period 1979-2001. Data on production is the most comprehensive, both across countries and over time so we use the production data to measure industrial production structure. The data on production is in current US dollars. For each country-year, we calculate the proportion of production in each of the 28 3-digit manufacturing sectors. Our measure of difference in industry structure is the sum of the squared differences in production shares between country-pairs i and j at time t, where the summation is carried out over the 28 manufacturing sectors.

$$\textit{Difference in Industry Structure}_t^{i,j} = \mathbf{a}'_{ij,t}\mathbf{a}_{ij,t} = \sum_{k=1}^{28} \left(pshare_{kt}^i - pshare_{kt}^j\right)^2$$

k is the index for the 28 manufacturing sectors, and

$$pshare_{kt}^i = \frac{prod_{kt}^i}{\sum\limits_{k=1}^{28} prod_{kt}^i}$$

is the production share in the k^{th} manufacturing sector and $prod_{kt}^i$ is the production in sector k in country i at time t. Countries with the same structure of production will have a value

[7] As a robustness check, we expanded the 12 month window to a 60 month rolling window. The results are qualitatively similar for the correlations calculated with the 60 month overlapping window.

of 0 for this index. Differences in industrial structures will be reflected in higher values of the index and for countries that specialize only in one industry (which is different from the industry of the other country in the pair), the index will attain its maximum value of 2.[8]

In the second step, we calculate the variance-covariance matrix of sector-specific shocks. Using annual data on industry-level value added per worker growth from the UNIDO database over 1979-2001, we construct a cross-sectoral variance-covariance matrix using the following procedure (see Koren and Tenreyro, 2007, for details). Let y_{ikt} be the growth rate of value added per worker in country i, sector k, in year t. We control for long-run differences in value added growth across countries in each sector, by demeaning y_{ikt} using the mean growth rate for each country and sector over the entire time period.

$$\widetilde{y}_{ikt} = y_{ikt} - \frac{1}{T}\sum_{Y=1}^{T} y_{ikt}$$

Next for each year and sector we calculate the cross-country average of growth in value-added per worker.

$$Y_{kt} = \frac{\sum_{i=1}^{C} \widetilde{y}_{ikt}}{C}$$

where C is the set of countries. Y_{kt} is a time series of the average growth for each sector, and can be thought of as a global sector-specific shock. Using these time series, we calculate the sample variance for each sector, and the sample covariance for each combination of sectors along the time dimension. This results in a time- and country-invariant 28 x 28 variance-covariance matrix of sectoral shocks, which we call Ω. The diagonal terms in Ω are simply the variance of sectoral shocks, with petroleum refineries and miscellaneous petroleum products as the two most volatile sectors (variance slightly higher than 0.01) and manufacturing of transport equipment as the least volatile (variance equal to 0.003).

[8] The online appendix provides a complete list of the countries included in our sample, the list of the 28 manufacturing sectors included in our calculations and various summary statistics and empirical distributions of these measures to show substantial differences in the industrial structure between country-pairs and within country-pairs over time.

Combining Ω with the vector of difference in production shares $\mathbf{a}_{ij,t}$ and the annual standard deviation of stock returns for country i and j, we obtain the risk-adjusted difference in production $\frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$ This variable takes into account not simply the squared differences in the production sector but also sector-specific volatility and covariance structure of sectoral shocks. This variable ranges from a low of 0.0004 between France and Spain in 1987 to a high of 1.18 between Oman and South Africa in 2000.

3.3 Specification and controls

The main regression is:

$$\rho_{ijt} = \alpha + \beta \frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}} + \gamma' Z_{ijt} + e_{ijt} + \tau_t \tag{2}$$

The dependent variable ρ is the conditional or unconditional annual pairwise correlation of monthly stock index excess returns for 58 countries from 1975 to 2000. The main coefficient of interest is β, which captures the effect of risk-adjusted differences in industrial structure on cross-country correlations. This coefficient is related to the parameter λ, which captures the transmission of value-added shocks to stock returns.

To ensure that the estimated β is not unduly influenced by omitted variables, we include a vector of controls (Z_{ijt}). First, from equation (1), all specifications include a variable $\left(\sigma_{it}^2 + \sigma_{jt}^2\right)/\sigma_{it}\sigma_{jt}$ where σ_{it} is the standard deviation of the returns in country i in year t. We separate this volatility measure from our main variable of interest, because our goal is to estimate the direct effect of differences in production structure on stock correlations without the confounding effect of volatility. Second, drawing on the literature of bilateral equity flows we include a series of bilateral variables. Martin and Rey (2004) derive a gravity model of bilateral flows of assets, which demonstrates the importance of size of economies and transaction costs for these cross-border flows. Their model is consistent with recent empirical evidence on bilateral cross-border equity flows in Portes and Rey (2005). They show that such flows depend positively on a measure of country size (measured by market capitalization) and negatively on transaction costs and informational frictions (proxied by distance). Therefore, we control for country size and stock market development using the product of stock market capitalization, and include the geographic distance between capital cities of country-pairs.[9] Third, we include a variable (same-region dummy) that takes the value 1 if the two countries are from the same region.[10] Next, we measure country pair integration using data on bilateral trade flows from IMF's Direction of Trade Statistics database. We operationalize this variable as the average of bilateral export shares between pairs of countries. Another variable used to measure integration is a dummy variable that takes the value one if the two countries are part of a free trade area or a customs union since this facilitates the flow of goods and services between the two countries. To capture differences in degree of development, we add a control which equals the absolute difference in per capita GDP in constant international dollars from the World Development Indicators. We also control for differences in political institutions by including a dummy variable that takes the value one if both countries are classified as democracies, and zero otherwise. Following Giavazzi and Tabellini (2004) we classify a country as a democracy if it receives a positive Polity score. Data are from Polity IV Project that classifies countries on a scale of -10 to 10 with higher numbers indicating more democratic regimes (Marshall, Jaggers and Gurr, 2000). Finally, we control for aggregate shocks such as a world business cycle, movements in the world rate of interest, or global capital market shocks using year dummies (τ_t) , and control for region-specific shocks by interacting the same-region dummy with each of the year dummies.

Table 1 lists the summary statistics and the data source for each variable.

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[9] We experimented with distance between financial centers and got similar results.

[10] We use the World Bank's 8-fold regional classification. North America, Latin America, Western Europe, East Europe and Central Asia, East Asia and Pacific, South Asia, Middle East and North Africa, and Sub Saharan Africa.

4 Unconditional Correlations and the Structure of Production

First, we look at the relationship between unconditional correlations of excess stock returns and our measure of risk-adjusted differences in the production structure $\frac{\mathbf{a}'_{ij,t}\Omega\mathbf{a}_{ij,t}}{\sigma_{i,t}\sigma_{j,t}}$. These estimates are shown in Columns 1-3 of Table 2. All columns in Table 2 include time fixed effects. In column 1, we see a negative and significant coefficient on our main variable - it implies that correlation between country pairs is higher if they have a similar industry structure. Column 2 adds country-specific fixed-effects to column 1 (two dummies are added for each country pair) to capture unobserved time-invariant country characteristics. We find that even with country dummies, the risk-adjusted differences in production structure remain a significant driver of stock return correlations. As before, greater are the differences for any country-pair, lower are the correlations in the stock returns. Column 3 includes country-pair fixed effects so that the estimates are within-effects. It also includes the same-region dummy interaced with time dummies to capture all region-time specific shocks. The negative coefficient on risk-adjusted differences in production structure imply that country-pairs that have become similar in terms of industrial structure over time exhibit a higher degree of comovement in stock market returns. Inclusion of the time dummies interacted with the same–region dummy in column 4 implies that we can be fairly confident that our measure of industrial structure is not simply a proxy for common region-specific shocks that arise out of geographic specialization of production.

In terms of the magnitude of effects, we find that for the estimates in column 1 (3), a one standard deviation reduction in the risk-adjusted measure difference in the structure of production raises unconditional correlations by 0.02 (0.01). A way to understand the magnitude of effects is to consider two country pairs, one of which has similar production structure and another pair that has very different production structures. In 1988, the variable *Risk-Adjusted Difference in Production Structure* takes the value 0.12 for the pair (USA, Pakistan) and the value 0.009 for (USA, UK). Our estimates in column 1 imply that if Pakistan's risk-adjusted production structure became identical to that of the UK, its correlation with the USA would rise by 0.04. With an average correlation of 0.07 for (USA, Pakistan) this amounts to more than a 50% increase in the magnitude of correlations.

For our control variables, we find that countries with similar levels of stock market development, at similar levels of development in terms of per capita GDP, and that have democratic political institutions exhibit higher comovements in stock returns. The difference in per capita GDP is not significant in the within-estimates in column 6 of Table 2. This implies that what matters for rising correlations over time is not whether country-pairs become similar in terms of per capita incomes but that they become similar in terms of their risk-adjusted structure of production. We also find county-pairs that are geographically proximate to each other, those that exhibit a higher degree of bilateral trade, and who are members of a common free trade area have larger stock return correlations. Free trade areas imply higher stock market comovements for both the pooled OLS and within-estimates while bilateral trade seems to play a role only in the pooled OLS specifications. Finally, stock markets of countries from the same region tend to move together. Our explanatory variables account for 23-36% of the variation in correlations across country-pairs and all models are jointly significant at the 1% level.

5 Conditional Correlations and the Structure of Production

So far we have focused on unconditional correlations and shown that these are significantly influenced by differences in industrial structure. However, as Longin and Solnik (1995) argue, even if the conditional correlations are constant, unconditional correlations tend to be very unstable over time and that this could be driven solely by time variation in market expected returns and variances.[11] First, expected returns may depend on worldwide and region-specific variables. Moreover the level of integration of national equity markets differs across countries and may change over time. Some countries are more integrated with the rest of the world and their returns are likely to be highly correlated. Similarly, countries within the same region may be more integrated and may have similar production structures (due to similar endowments). Growing international and/or regional integration over time could also lead to a progressive increase in market correlation. Second, the variance of returns may be heteroskedastic. In fact, the conditional variance of national equity markets has been modelled with good success using a univariate GARCH approach for several national markets. And if these changes in volatility coincide with changes in industrial structure, then our estimates will be biased and inconsistent. For all these reasons, it is important to consider also conditional correlations.

As a next step we take an asset pricing perspective and estimate two asset pricing models. The first is the Fama-French three factor model and the second is a two-factor model with time-varying factor loadings where one is a common world factor and the other is a regional factor. We use the parsimonious factor model proposed by Fama and French (1998) to capture style exposures in an international context. The world Fama-French model, has three factors, a world market factor, a size factor (WSMB) and a value factor (WHML). The model in Fama and French (1998) only has the world market factor (μ_τ^W) and the value factor ($WHML_\tau$), the data for which is available from Kenneth French.[12] In addition, we also include factors that are specific to the US which is the world's largest stock market. For

[11] Longin and Solnik (1995), model the asset return dynamics explicitly using a bivariate GARCH model for each pair of markets and condition the first two moments of the distribution on a set of information variables. This is their baseline model for the null hypothesis of constant conditional correlation. However, they also reject the null of constant conditional correlation.

[12] Like Fama and French (1998) we are relying on MSCI data. They show that such a database of large stocks does not allow meaningful tests for a size effect. Therefore, they restrict themselves to the world value factor.

the US, we include the excess return in the US (μ_τ^{US}), a US size factor ($USSMB_\tau$) and a US value factor ($USHML_\tau$). We estimate the following excess return equation using monthly data

$$\begin{aligned} R_{i\tau} &= \beta_i^W \mu_\tau^W + \beta_i^{US} \mu_\tau^{US} + \beta_i^{WHML} WHML_\tau \\ &\quad + \beta_i^{USSMB} USSMB_\tau + \beta_i^{USHML} USHML_\tau + e_{i\tau} \\ &\quad e_{i\tau} \sim N(0, \sigma_{i\tau}^2) \\ \sigma_{i\tau}^2 &= a_i + b_i \sigma_{i\tau-1}^2 + c_i e_{i\tau-1}^2 + d_i \left[\max\left(0, e_{i\tau-1}\right)\right]^2 \end{aligned} \tag{3}$$

The variance of the idiosyncratic return shock in market i, $e_{i\tau}$ follows a GARCH process in eq. (3) with asymmetric effects in conditional variance, as in Glosten, Jagannathan, and Runkle (1993). Previous research such as Longin and Solnik (1995), Erb, Harvey, and Viskanta (1994) and De Santis and Gerard (1997) find different correlations in up and down markets and that volatility reacts in an asymmetric fashion to positive and negative news.

For the second factor model, we follow the setup of Bekaert and Harvey (1997) and Bekaert, Harvey and Ng (2005). This model in addition to the asymmetric GARCH specification, also incorporates time-varying factor loadings, where the factor loadings are influenced by trade patterns. Chen and Zhang (1997) and Bekaert, Harvey and Ng (2005) find that the crossmarket correlations of stock returns are related to external trade among countries. For each country, we estimate the following excess return equation

$$\begin{aligned} R_{i\tau} &= \beta_{i\tau}^W \mu_\tau^W + \beta_{i\tau}^{REG} \mu_\tau^{REG} + e_{i\tau} \\ &\quad e_{i\tau} \sim N(0, \sigma_{i\tau}^2) \\ \sigma_{i\tau}^2 &= a_i + b_i \sigma_{i\tau-1}^2 + c_i e_{i\tau-1}^2 + d_i \left[\max\left(0, e_{i\tau-1}\right)\right]^2 \end{aligned} \tag{4}$$

where μ_τ^W is the monthly excess return on a world portfolio, μ_τ^{REG} is the excess return on a regional portfolio and $e_{i\tau}$ is the idiosyncratic shock of any market i.[13] The sensitivity of each market i to the world and regional portfolios is measured by the time-varying parameters

[13] For the world index, we use the MSCI World Market Index. For the regional indices we use the Asia,

$\beta_{i\tau}^{W}$ and $\beta_{i\tau}^{REG}$. These time-varying parameters are modeled as depending in a linear fashion on trade patterns with $\beta_{i\tau}^{W}$ a function of country i's trade (exports plus imports) with the world as a whole, and $\beta_{i\tau}^{REG}$ a function of country i's trade (exports plus imports) with all the other countries in its region.[14] For each country, we use monthly data to estimate (3) and (4), extract the residual $\widehat{e}_{i\tau}$ in each specification and calculate the conditional correlations over each year.

Columns 1-3 in Table 3 shows how the Fama-French conditional correlations are affected by risk-adjusted differences in production structure. As with the unconditional correlations, we find that bigger the differences in production structure, lower are the stock market co-movements between pairs of countries. This result holds in a pooled OLS with time dummies, when we add country-fixed effects, as well as in a within-estimation with country-pair fixed effects and the same-region interacted with year dummies. Comparing the magnitude of the coefficients in Table 3 to that in Table 2 (that uses unconditional correlations), we see that the magnitude increases substantially across specifications, with the increase especially pronounced for the within-estimates in column 3. The pooled OLS estimates in Column 1 imply that a one standard deviation reduction in the risk-adjusted measure of structure of production, raises conditional correlations by about 0.05. When we add time and country-fixed effects, in columns 2 and 3, the coefficient declines but remains strongly significant. To get an idea of the magnitude of effects, consider the country pair (USA, Singapore). The risk-adjusted measure of difference in production structure takes the value 0.63 in the year

Middle East and Africa and Latin America indices from EMDB. For European countries we use the MSCI Europe Index, for Australia and New Zealand we use the MSCI Pacific Index, for Japan we use the Pacific Index excluding Japan, for Canada we use the US index. Finally, for the US given its overwhelming size in world markets we do not include any regional index. Note that the this regional classification is based on the MSCI data and is coarser that the World Bank's classification used to construct the dummy variable "same region."

[14]Since data on trade are available only on an annual basis, the time-variation in the $\beta's$ is effectively on an annual basis.

1977 and 0.01 in the year 1999, underlying which is an unprecedented transformation in the industrial structure of Singapore. The within-estimate of the coefficient on the risk-adjusted measure of difference in production structure equals -0.745 in Table 3. This implies an increase in the correlation between the stock returns in Singapore and USA by 0.46. This is a substantial increase in correlation, which will necessitate a significant reshuffling of portfolio allocations across these two markets. Although in the mid-1970s investing in Singapore might have given US investors significant diversification benefits, today this cross-country diversification will yield much smaller gains in reducing the overall portfolio variance. Importantly, the reason for this change in cross-country diversification benefits is the change in the industrial structure in Singapore.

Columns 4-6 examines the conditional correlations based on the international and regional CAPM model with time varying betas. Once again across specifications, we find that countries who specialize and produce in different manufacturing sectors tend to exhibit lower conditional correlations. The relationship holds for the pooled OLS, with and without country fixed-effects and for the within-effects over time. Once again there is a marked increase in the magnitude of the coefficients as compared to those in Table 2, with more than a doubling for the pooled OLS and a trebling for the within-effects estimates. The explanatory power of our variables range from 24% for the pooled OLS without any fixed effects to 39% for the within-estimates that includes country-pair and same-region year dummies.

6 Extensions and Robustness

6.1 Developed vs. Developing Countries

One possible criticism of our results is that a particular subset of country-pairs is primarily responsible for the negative relationship between differences in production structure and stock market correlation - that this relationship holds only for country-pairs where one is a developed country and the other a developing country. To examine this possibility,

Table 6 presents regression results, taking various permutations in the choice of country-pairs in the sample. Column 1 restricts the sample to country-pairs where both countries are developing countries; Column 2 uses the sample of pairs, where one is developed and the other developing; Column 3 restricts the sample to developed country-pairs. We use the World Bank classification for developed vs. developing countries. Across these various sub-samples, we find evidence for a negative relation between risk-adjusted differences in the structure of production and conditional stock market correlations (based on the Fama-French model). In terms of both statistical significance and magnitude of effect, the relationship is strongest for country-pairs where one is developed and one is developing. However, the relationship holds for the other two sub-samples as well, with almost equally strong results for the sub-sample where both countries are developed. This attests to the robustness of this relationship.

Next, we used standard portmanteau tests to check for autocorrelation in the dependent variables. Only 8% of the country-pairs for unconditional correlations and 4-6% of the country-pairs for conditional correlations exhibit autocorrelation. However, our results are robust to the deletion of these variables. Please see the Online Apendix for tables with these restricted sub-samples.

6.2 Segmentation vs. Integration

The literature on international stock market comovements analyzes also the effect of financial liberalization for correlations and more generally it studies trends in financial integration (e.g. Bekaert and Harvey, 2000; Bekaert, Hodrick, and Zhang, 2005). If financial markets are integrated, then the degree of correlation will be affected more by investors' preferences and other demand-driven idiosyncratic factors. Analogously, variations in segmented markets will be driven more by local investors and by industry-specific shocks. We test this hypotheses in Table 7. We use data on stock market liberalization dates from Bekaert, Harvey and Lundblad (2005). Using this data we created two dummy variables – one for cases when one market is integrated (liberalized) while the other is segmented and a dummy variable that takes a value of 1 when both markets are segmented. The default option captured by the constant term is when both markets are liberalized. Our interest is to see how the role of industrial structure changes with financial liberalization. To estimate this effect we include our measure of risk-adjusted production structure and the interaction of this variable with the two dummy variables capturing the state of financial liberalization. Column 1 of Table 7 shows that industrial differences still remain an important explanatory variable for cross-country stock comovements, but the effect differs depending on the level of integration. While the coefficient on industrial structure for two liberalized economies is -0.724, for countries where at least one of the markets is segmented the coefficients increases in absolute value by about 1.5 to -1.684. In other words, industrial structure differences matter much more for countries that do not have liberalized financial markets.

In the last two columns we investigate the effect of financial liberalization over time. Column 2 includes a dummy variable that takes the value of 1 once a country-pair has transited to integrated stock markets. Column 3 includes both this dummy variable and its interaction with risk-adjusted industrial structure.[15] In both cases liberalization raises cross-markets correlations by about five percentage points. Differences in industrial structure still explains conditional correlations, but the coefficient on the interaction term in column 3 shows that its role changes very little in the post-liberalization period.[16]

[15] Columns 2 and 3 include time fixed effects and country-pair fixed effects. The dummy variable captures the event when a pair of countries made the transition to a situation where both can be classified as having integrated stock markets. It takes the value 1 in all years after both countries had made a switch to liberalized stock markets. It takes the value 0 if either country has a segmented market or if both countries had liberalized stock markets on or before 1975.

[16] We get very similar if we use the conditional correlations based on the international and regional CAPM model.

7 Conclusion

In this paper we have focused on the role of industry-specific shocks in explaining cross-country comovements in stock market indices. We have documented that differences in industrial structure across pairs of countries are significant and robust predictors of stock market correlations. This finding can be rationalized in models where the stochastic component of stock market returns is affected directly by industry-specific shocks, which then influence the overall stock market return through the share that this industry takes in the overall economic activity in the country. Thus, we show that fundamentals as captured by idiosyncratic sectoral shocks do explain comovements in stock market indices.

There are two issues that arise from the results in this paper. First, the explanatory power of industrial structure is always statistically significant but it is not overwhelming on average – for average changes in industrial structure we explain about five percentage points of pairwise correlations. There are examples, however, where industrial structure seems to matter more. For Singapore and the US, the actual change in production structure raises correlations by forty-six percentage points. When we look at the average economic significance, one of the reasons for the low explanatory power is that we do not investigate industry-specific portfolios. One can use the methodology of the paper to investigate to what extent cross-country correlations of industry-based portfolios are explained by industry specific shocks. Second, we do recognize that to have a more complete explanation of the observed correlations, one has to go beyond the production side and analyze also the role capital controls, liquidity fluctuations, regulation, etc. and in particular their relationship to the role of the industrial structure. Some of these topics have been already discussed in the literature (e.g. Bekaert, Hodrick, and Zhang, 2005), others we leave for future research.

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Figure 1: Average Correlations for 26 pairs of Countries (1970-2006)

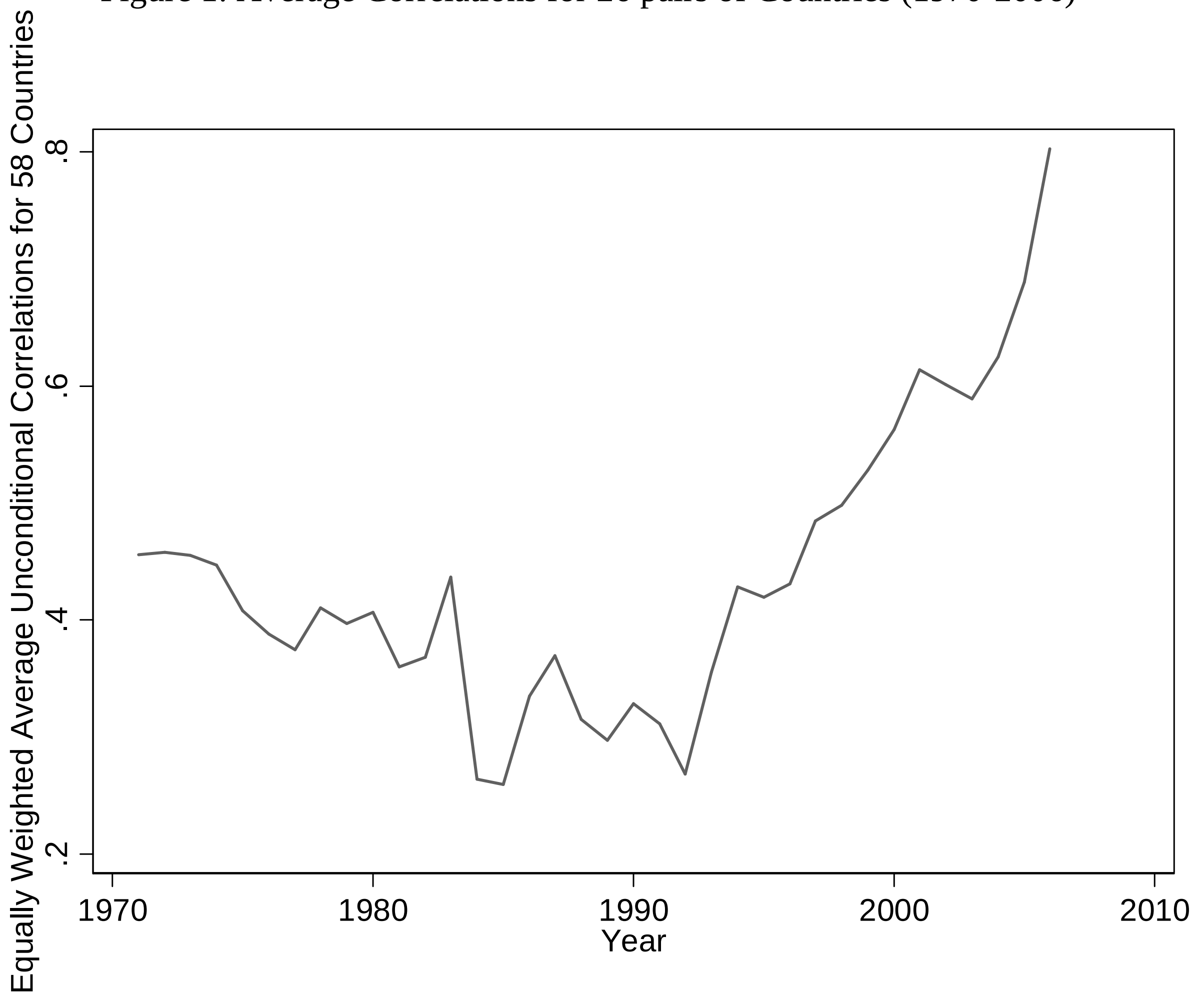

Table 1: Variables, Summary Statistics and Data Sources

Variable	*N*	*Mean*	*Std. Dev.*	*Data Source*
Unconditional correlations	27446	0.277	0.347	MSCI and EMDB databases
Conditional correlations (Fama-French)	22443	0.312	0.338	MSCI and EMDB databases; Fama-French website
Conditional correlations (International+Regional CAPM)	19423	0.297	0.328	MSCI and EMDB databases
Risk-adjusted difference in production structure	15945	0.030	0.056	UNIDO database
Product of stock market capitalization (logged)	36649	-2.771	2.149	Database of Financial Sector Development World Bank
Difference in per capita GDP	49292	1.031	0.807	World Development Indicators, World Bank
Dummy =1 if both countries are democratic	58339	0.457	0.498	Polity IV Project
Distance (logged)	95874	8.616	0.922	www.cepii.org
Average of bilateral trade as a proportion of total trade	70638	0.017	0.053	Direction of Trade Statistics, IMF
Dummy =1 if countries from the same region	95874	0.157	0.364	www.cepii.org
Dummy =1 if countries are members of FTA or Customs Union	75100	0.061	0.239	www.cepii.org

Table 2: Stock Market Correlations and Risk-Adjusted Differences in Structure of Production

	(1) Unconditional correlation	(2) Unconditional correlation	(3) Unconditional correlation
risk-adjusted difference in production structure	-0.318***	-0.159**	-0.175**
	(0.062)	(0.074)	(0.072)
product of stock market capitalization	0.032***	0.021***	0.021***
	(0.002)	(0.004)	(0.004)
difference in per capita GDP	-0.040***	-0.049***	0.028
	(0.003)	(0.004)	(0.019)
both democracies	0.070***	0.061***	0.063***
	(0.006)	(0.010)	(0.011)
average of bilateral export shares	0.325***	0.227***	0.062
	(0.051)	(0.065)	(0.156)
free trade area	0.122***	0.057***	0.072***
	(0.010)	(0.011)	(0.018)
distance	-0.009**	-0.024***	
	(0.004)	(0.006)	
same region	0.059***	0.036***	
	(0.009)	(0.011)	
$(\sigma_{it}^{2} + \sigma_{jt}^{2})/ \sigma_{it}\,\sigma_{jt}$	-0.017***	-0.024***	-0.019***
	(0.003)	(0.003)	(0.002)
Observations	15066	15066	15066
R-squared	0.23	0.29	0.36
Joint significance test	159.15***	57.81***	48.56***
Time fixed effects	Yes	Yes	Yes
Country fixed effects	No	Yes	No
Pair fixed effects	No	No	Yes
Same region*time fixed-effects	No	No	Yes

Standard errors in parentheses are adjusted for clustering on country-pairs; * significant at 10%; ** significant at 5%; *** significant at 1%
The dependent variable is the unconditional correlation of monthly stock market excess returns over each year.
For each year, the correlation for country-pairs is calculated over a 12-month horizon. σ_{it} is the annual standard deviation of the stock returns for county *i*.

Table 3: Conditional Stock Market Correlations and Risk-Adjusted Differences in Structure of Production

	(1)	(2)	(3)	(4)	(5)	(6)
	Fama-French	Fama-French	Fama-French	International & Regional CAPM	International & Regional CAPM	International & Regional CAPM
risk-adjusted difference in production structure	-0.900***	-0.588***	-0.745***	-0.778***	-0.368**	-0.495***
	(0.111)	(0.134)	(0.140)	(0.150)	(0.184)	(0.159)
product of stock market capitalization	0.042***	0.028***	0.025***	0.043***	0.028***	0.025***
	(0.002)	(0.004)	(0.005)	(0.002)	(0.004)	(0.005)
difference in per capita GDP	-0.048***	-0.047***	0.000	-0.047***	-0.048***	-0.016
	(0.004)	(0.005)	(0.033)	(0.004)	(0.005)	(0.034)
both democracies	0.023***	0.087***	0.085***	0.023***	0.091***	0.087***
	(0.008)	(0.015)	(0.016)	(0.008)	(0.015)	(0.016)
average of bilateral export shares	0.336***	0.265***	0.157	0.357***	0.276***	0.189
	(0.051)	(0.065)	(0.171)	(0.051)	(0.064)	(0.164)
free trade area	0.113***	0.055***	0.059***	0.110***	0.059***	0.063***
	(0.010)	(0.012)	(0.019)	(0.010)	(0.012)	(0.018)
distance	-0.000	-0.018***		-0.004	-0.019***	
	(0.005)	(0.006)		(0.005)	(0.006)	
same region	0.063***	0.039***		0.059***	0.035***	
	(0.009)	(0.012)		(0.009)	(0.012)	
$(\sigma_{it}{}^{2} + \sigma_{jt}{}^{2})/\sigma_{it}\,\sigma_{jt}$	-0.034***	-0.035***	-0.039***	-0.036***	-0.037***	-0.041***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	11456	11456	11456	11451	11451	11451
R-squared	0.24	0.32	0.39	0.24	0.32	0.39
Joint significance test	140.92***	49.85***	45.09***	137.89***	50.09***	49.94***
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	No	Yes	No	No	Yes	No
Pair fixed effects	No	No	Yes	No	No	Yes
Same region*time fixed-effects	No	No	Yes	No	No	Yes

Standard errors in parentheses are adjusted for clustering on country-pairs; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable is the conditional correlation of monthly stock market excess returns over each year. Columns 1-3 use the Fama-French model to calculate the conditional correlations; Columns 4-6 use the CAPM model to calculate the conditional correlations; For each year, the correlation for country-pairs is calculated over a 12-month horizon.
All columns include a constant (not shown). σ_{it} is the annual standard deviation of the Fama-French or CAPM residuals.

Table 4: Conditional Stock Market Correlations and Risk-Adjusted Structure of Production (country sub-samples)

	(1)	(2)	(3)
	Both developing countries	One developed, one developing	Both developed countries
risk-adjusted production structure difference	-0.885*	-1.550***	-1.117***
	(0.539)	(0.146)	(0.181)
product of stock mkt. capitalization	0.026***	0.041***	0.047***
	(0.005)	(0.003)	(0.003)
difference in per capita GDP	0.012	-0.026***	-0.190***
	(0.015)	(0.007)	(0.023)
both democracies	0.044***	0.005	-0.049**
	(0.016)	(0.011)	(0.020)
average of bilateral export shares	0.737*	0.120	0.281***
	(0.433)	(0.090)	(0.065)
free trade area	0.168***	0.193***	0.035**
	(0.039)	(0.022)	(0.014)
distance	0.038***	0.021***	-0.040***
	(0.013)	(0.008)	(0.007)
same region	0.162***	0.033	0.013
	(0.029)	(0.020)	(0.014)
$(\sigma_{it}^{\,2} + \sigma_{jt}^{\,2})/\,\sigma_{it}\,\sigma_{jt}$	-0.052***	-0.013***	-0.077***
	(0.007)	(0.005)	(0.012)
Observations	1962	4926	4563
R-squared	0.11	0.08	0.14
Joint significance test	25.65***	48.07***	97.22***

Standard errors in parentheses are adjusted for clustering on country-pairs; * significant at 10%; ** significant at 5%; *** significant at 1%. The dependent variable is the conditional correlation of monthly stock market excess returns over each year. We use the Fama-French model to calculate the conditional correlations. All columns include a constant (not shown). σ_{it} is the annual standard deviation of the Fama-French residuals.

Table 5: Conditional Stock Market Correlations and Structure of Production (Segmentation vs. Integration)

	(1)	(2)	(3)
	Fama-French	Fama-French	Fama-French
Risk-adjusted difference in production structure	-0.724***	-0.734***	-0.691***
	(0.103)	(0.142)	(0.183)
one integrated and one segmented market	0.021**		
	(0.009)		
*one integrated & one segmented market*Risk-adjusted production structure difference*	-1.684***		
	(0.291)		
both segmented markets	0.028		
	(0.026)		
both segmented markets risk-adjusted production structure difference*	-1.554**		
	(0.733)		
stock market liberalization dummy		0.050***	0.052***
		(0.012)	(0.013)
*stock market liberalization dummy*risk-adjusted production structure difference*			-0.088
			(0.229)
product of stock mkt. capitalization	0.042***	0.026***	0.026***
	(0.003)	(0.005)	(0.005)
difference in per capita GDP	-0.046***	-0.032	-0.034
	(0.004)	(0.034)	(0.034)
both democracies	0.023***	0.087***	0.087***
	(0.008)	(0.016)	(0.016)
average of bilateral export shares	0.330***	0.095	0.097
	(0.051)	(0.164)	(0.164)
free trade area	0.115***	0.055***	0.055***
	(0.010)	(0.018)	(0.018)
distance	-0.0003		
	(0.005)		
same region	0.061***		
	(0.010)		
$(\sigma_{it}^{2} + \sigma_{jt}^{2})/\sigma_{it}\,\sigma_{jt}$	-0.034***	-0.038***	-0.038***
	(0.004)	(0.004)	(0.004)
Observations	11456	11456	11456
R-squared	0.25	0.39	0.39
Joint significance test	126.89***	81.87***	79.42***
Time fixed effects	Yes	Yes	Yes
Country-pair fixed effects	No	Yes	Yes
Test: coeff [prod. structure difference] + coeff [one integrated one segmented markets*production structure difference] = 0	74.9***		
Test: coeff [prod. structure difference] + coeff [one segmented markets*production structure difference] = 0	9.84***		

Standard errors in parentheses are adjusted for clustering on country-pairs; * significant at 10%; ** significant at 5%; *** significant at 1%; The dependent variable is the conditional correlation of monthly stock market excess returns over each year. We use the Fama-French model to calculate the conditional correlations. All columns include a constant (not shown). σ_{it} is the annual standard deviation of the Fama-French residuals. The "both integrated" dummy =1 if both markets are integrated; "one integrated" dummy =1 if exactly one of the country-pairs is integrated while the other is segmented. The both segmented dummy =1 if both markets are segmented. The stock market liberalization dummy takes the value 1 in all years after both countries had made a switch to liberalized stock markets. It takes the value 0 if either country has a segmented market or if both countries had liberalized stock markets on or before 1975. Stock market liberalization dates are from Bekaert et al (2005).