The Information Content of Stock Markets:

Why Do Emerging Markets Have Synchronous Stock Price Movements?

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Abstract

Stock prices move together more in poor economies than in rich economies. This finding is not due to market size and is only partially explained by higher fundamentals correlation in low-income economies. However, measures of property rights do explain this difference. The systematic component of returns variation is large in emerging markets, and appears unrelated to fundamentals co-movement, consistent with noise trader risk. Among developed economy stock markets, higher firm-specific returns variation is associated with stronger public investor property rights. We propose that strong property rights promote informed arbitrage, which capitalizes detailed firm-specific information.

1. Introduction

Stock returns reflect new market-level and firm-level information. As Roll (1988) makes clear, the extent to which stocks move together depends on the relative amounts of firm-level and market-level information capitalized into stock prices. We find that stock prices in economies with high per capita gross domestic product (GDP) move in a relatively unsynchronized manner. In contrast, stock prices in low per capita GDP economies tend to move up or down together. A time series of stock price synchronicity for the U.S. market also shows that the degree of co-movement in U.S. stock prices has declined, more or less steadily, during the 20th century. These findings are not due to differences in market size or economy size.[1]

We consider three plausible explanations for our finding. First, firms in low-income countries might have more correlated fundamentals, and this correlation might make their stock prices move more synchronously. For example, if low-income economies tend to be undiversified, firm-level earnings may be highly correlated because industry events are essentially market-wide events. Second, low-income economies often provide poor and uncertain protection of private property rights. Political events and rumors in such countries could, by themselves, cause market-wide stock price swings. Moreover, inadequate protection for property rights could make informed risk arbitrage in their stock markets unattractive. According to De Long et al. (1989, 1990), a reduction in informed trading can increase market-wide noise trader risk, which we would observe as increased market-wide stock price variation unrelated to fundamentals. Third, in countries that provide poorer protection for public investors from corporate insiders, problems such as intercorporate income shifting could make firm-specific information less useful to risk arbitrageurs, and therefore impede the capitalization of firm-specific information into stock prices. This effect would reduce firm-specific stock price variation, again increasing stock return synchronicity.

We reject the first hypothesis, and find some evidence consistent with the second and third hypotheses stated above. Our formal statistical analysis shows that economies with more correlated fundamentals do have stock markets with more synchronous returns, but our best efforts to control for fundamentals correlation and volatility do not render per capita GDP insignificant. Adding a variable that measures government respect for private property, however, does render per capita GDP insignificant in explaining stock price synchronicity. Finally, among developed economies, more protection of public shareholders' property rights against corporate insiders is correlated with more firm-specific information being capitalized into stock prices.

We conjecture that the degree to which a country protects private property rights affects both the extent to which information is capitalized into stock prices and the sort of information that is capitalized. While our econometric evidence is consistent with this conjecture, we recognize that our explanation is incomplete. We invite alternative explanations of our empirical finding that stock returns are synchronous in low-income economies and asynchronous in high-income economies. Any such explanations must be consistent with our findings that market size, economy size, and many aspects of fundamentals volatility do not affect the relation between per capita GDP and synchronicity, but that measures of property rights protection render per capita GDP insignificant in explaining stock price synchronicity.

In the next section, we review the empirical regularities that motivate this research. In Section 3, we develop our basic synchronicity measures and show their negative relationship with per capita GDP. In Section 4, we discuss our empirical framework and the dependent variables we adopt. In the fifth, sixth and seventh sections, we present our hypotheses and empirical specifications, report our results, and conduct various robustness checks. In Section 8, we present conclusions.

2. Emerging markets and developed economies

Table 1 compares the synchronicity of stock returns in some representative stock markets during the first 26 weeks of 1995. Data from other periods in the 1990s display similar patterns. In emerging markets like China, Malaysia, and Poland, over 80% of stocks often move in the same direction in a given week. In Poland, 100% of traded stocks move in the same direction during four of the twenty six weeks. In contrast, Denmark, Ireland, and the United States lack any instances of more than 57% of the stocks moving in the same direction during any week, despite a rising market in the United States. Figure 1 contrasts Chinese, Malaysian and Polish stocks with U.S. stocks. For clarity, Fig. 1 omits the data for Denmark and Ireland. As Table 1 shows, the stocks data for Denmark and Ireland closely resemble the returns in the U.S. market.

We can easily reject the trivial explanation based on the Law of Large Numbers that markets with many stocks should show less dispersion around the mean. First, the stock markets of Denmark and Ireland resemble the U.S. market, despite listing substantially fewer securities than China or Malaysia. Below we shall show that stock price co-movement is negatively correlated with per capita income, regardless of market or economy size. Second, the contrast between the U.S. market and emerging markets is too stark to be based solely on a statistical artifact. To test these differences, we calculate

$$f_{jt} = \frac{\max[n_{jt}^{up},\ n_{jt}^{down}]}{n_{jt}^{up} + n_{jt}^{down}}, \tag{1}$$

where n_{jt}^{up} is the number of stocks in country j whose prices rise in week t and n_{jt}^{down} is the number of stocks whose prices fall. For each country j we calculate f_{US} - f_j. The variance of the estimate is approximately

$$\frac{f_{US}(1 - f_{US})}{n_{US}} + \frac{f_j(1 - f_j)}{n_j}, \tag{2}$$

assuming that f_{US} and f_j are uncorrelated. By the Central Limit Theorem, the statistic

$$\frac{(f_{US} - f_j)}{\sqrt{f_{US}(1 - f_{US})/n_{US} + f_j(1 - f_j)/n_j}} \tag{3}$$

is approximately normal for sufficiently large sample sizes such as n_{US} and n_j. The null hypothesis that the fraction of stocks moving together in the U.S. is the same as that in the emerging markets can be rejected in 43 out of 52 weeks for China, 37 weeks for Poland, and 45 weeks for Malaysia. In contrast, the null hypothesis can be rejected in only 18 weeks for Denmark and New Zealand, and in only 2 weeks for Ireland.

The differences are economically as well as statistically significant. Using the weekly data for the whole of 1995, Eq. (1) shows that 79% of the stocks in China move together in an average week. The same calculation indicates that 77% of the stocks in Malaysia move together in an average week of 1995, as do 81% of the stocks in Poland. In contrast, in the United States, Denmark, and Ireland, the fraction of stocks gaining value in a given week typically barely exceeds the fraction of stocks losing value.

The United States as an Emerging Economy?

Figure 2 plots the fraction of U.S. stocks that move together in a given month, excluding stocks whose prices do not move, over the period 1926 to 1995. In the earlier half of this period, the fraction of stocks that move together is comparable to the fractions for emerging markets displayed in Table 1. Fig. 2 demonstrates that price synchronicity decreased as the U.S. economy developed.

The number of stocks traded in the U.S. has increased over time, so the fraction moving together should fall towards the theoretical mean of approximately 50% that would prevail were monthly returns approximately zero and independent. Figure 2 addresses this problem by graphing the fraction of 400 stocks, randomly selected each period, that move together each month. The same decline remains apparent. The decline in synchronicity in U.S. stock prices is not due to the increase in the number of traded stocks.

As a robustness check, we develop an alternative measure of stock price synchronicity using the linear regression

$$r_{it} = \alpha_i + \beta_i \, r_{mt} + \varepsilon_{it}, \tag{4}$$

where $r_{i,t}$ is stock i's return in week t, and $r_{m,t}$ is a market index return. A high R^2 in such a regression indicates a high degree of stock price synchronicity. Our thinking is akin to Roll (1988), who examines this regression statistic for individual stocks in the U.S. We expand on this point when we introduce our formal measures of stock price synchronicity, below. Figure 3 graphs the average R^2 for Eq. (4) across stocks, based on monthly returns, for each non-overlapping 5-year period from 1926 to 1995. Fig. 3 was constructed first using data for all available stocks, and then using the largest 300 stocks only. The latter is based on rankings at the beginning of each 5-year period, and uses an equally weighted market index based on those stocks only. A decline in both R^2s from the 1930s to the present is apparent, demonstrating again that the behavior of U.S. stock prices earlier in the twentieth century was similar to that of emerging market stock prices now.

3. Two stock price synchronicity measures

A simple and direct measure of synchronicity in stock price movements is a formalization of the discussion surrounding Table 1. We therefore calculate the fraction of stocks that move in the same direction in country *j*,

$$f_j = \frac{1}{T}\sum_t \frac{\max[n_{jt}^{up},\ n_{jt}^{down}]}{n_{jt}^{up} + n_{jt}^{down}} = \frac{1}{T}\sum_t f_{jt}. \tag{5}$$

In Eq. (5), n_{jt}^{up} is the number of stocks in country *j* whose prices rise in period *t*, n_{jt}^{down} is the number of stocks whose prices fall, and *T* is the number of periods used. We drop stocks whose prices do not move to avoid bias due to non-trading. Thus, we define f_j as the average value of f_{jt}, as defined in Eq. (1), across periods. Values of f_j must lie between 0.5 and 1.0.

Table 2 juxtaposes the ranking of countries by *per capita* GDP in Panel A with their ranking by stock price synchronicity, as measured by f_j, in Panel B. Generally, high-income countries have asynchronous stock prices, and the U.S. has the lowest fraction of stocks moving together, f_j. In contrast, low-income economies have the highest f_js. The five highest f_js are for Poland, China, Taiwan, Malaysia, and Turkey. Our calculation of f_j, the fraction of stocks in each country that move together, are based on 1995 data. Our GDP per capita variable is averaged over 1992 to 1994 to mitigate any transitory noise. Using a three-year average of f_{jt} gives similar results to those shown in Table 2.

An alternative way to distinguish firm-specific stock price movements from market-wide price movements, following French and Roll (1986) and Roll (1988), both of whom use U.S. data only, is to calculate the R^2s of regressions of the form

$$r_{it} = \text{á}_i + \text{â}_{1,i}\, r_{m,jt} + \text{â}_{2,i}[r_{US,t} + e_{jt}] + \text{å}_{it}, \tag{6}$$

where *i* is a firm index, *j* a country market index, *t* a two-week period time index, $r_{m,jt}$ is a domestic market index, and $r_{US,t}$ is the U.S. market return. The rate of change in the exchange rate per U.S. dollar is e_{jt}.

The regression specified in Eq. (6) is similar to classical asset pricing equations. We do not pursue this asset pricing interpretation of Eq. (6) because we view the present paper as an application of Grossman's (1976) and Roll's (1988) approach to information capitalization, and not as a refinement or critique of any asset pricing model. Our emphasis is on the type of information that enters stocks prices, not on any tradeoff between risk and return.

We include the U.S. stock market return in Eq. (6) because most economies are at least partially open to foreign capital. The expression $r_{US,t} + e_{jt}$ translates U.S. stock market returns into local currency units. We use biweekly returns to overcome thin trading problems, which arise when securities are traded infrequently. These returns are compounded from daily total returns. For stock markets in the Far East, we lag U.S. market returns by one day to account for time zone differences. Thus, if the biweekly stock return in Japan used data from May 7, 1995 to May 21, 1995, the contemporaneous U.S. market return uses data from May 6, 1995 to May 20, 1995. When we calculate Eq. (6) using U.S. data, we set $\text{â}_{2,i}$ to zero.

Our daily with-dividend stock returns data begin with all companies covered by the *Datastream* information service as of January 1997. *Datastream* also allowed us access to data for companies no longer traded, but whose stock prices were formerly covered by their service. Our total cross section for 1995 thus contains 15,920 firms spanning 40 countries. Newly listed or recently delisted stocks are included in our sample only if more than 30 weeks of data is available for the year in question. This requirement yields sufficient observations to reliably assess the explanatory power of the market returns on each stock. Thus, we omit newly traded stocks that have been traded for roughly less than five months in a year, as well as stocks that are about to be delisted. When trading of a stock is suspended, the returns data during the suspension period are coded as missing and also excluded from our regressions. In addition, for most countries, *Datastream* returns are either unavailable or seriously incomplete until the mid-1990s. For this reason, we focus on 1993 through 1995, and use only 1995 data in our international cross-sectional analysis. As a robustness check, we reproduce our results using 1993 and 1994 data.

Datastream claims that its total returns are adjusted for splits and other unusual events, but our data do contain some very large stock returns. If these very large returns reflect coding errors, they could add noise to our data or create bias in our results. On the assumption that coding errors are over-represented in extreme observations, we trim our data by dropping biweekly observations for which the stock's return exceeds 0.25 in absolute value.

The regression statistic for Eq. (6), R_{ij}^2, measures the percent of the variation in the biweekly returns of stock i in country j explained by variations in country j's market return and the U.S. market return. Given this statistic for each firm i in country j, we define

$$R_j^2 = \frac{\sum_i R_{i,j}^2 \times SST_{i,j}}{\sum_i SST_{i,j}} \tag{7}$$

as an alternative stock price synchronicity measure, where $SST_{i,j}$ is the sum of squared total variations. We use this weighting rather than a simple average to facilitate the decomposition of returns variation in Eqs. (16) and (17) (see in Section 6). A higher R_j^2 indicates that stock prices frequently move together. This measure of stock price synchronicity follows Roll (1988) and French and Roll (1986).

Panel C of Table 2 juxtaposes the ranking of countries by stock price synchronicity, as measured by R_j^2, against their ranking by per capita GDP in Panel A. Only four relatively wealthy countries have notably high R^2s. These countries are Japan, Italy, Greece, and Spain. Note that the stock market in Japan is regarded by many practitioners as notoriously bubble-prone, and that Italy has a demonstrably poorly functioning stock market (see Zingales, 1994). With these exceptions, low-income economies account for the high R^2s. The five highest R_j^2s are for Poland, China, Malaysia, Taiwan, and Turkey. The five lowest R^2s are for developed high-income countries - the United States, Ireland, Canada, the United Kingdom, and Australia. Overall, the R_j^2 estimates for high-income countries tend to be below the median.[2]

Figures 4 graphically highlights the large differences across countries in the f_j and R_j^2 measures of stock market synchronicity. Panel A of Figure 5 plots the f_j of each country against the logarithm of its per capita GDP, illustrating a clear and statistically significant negative correlation equal to -0.571 and significant at the 0.1% level. Panel B of Figure 5 plots each country's R_j^2 against the logarithm of its per capita GDP, again making evident a clear and significant negative correlation of -0.394, significant at the 2% level. A closer look at Figure 5 suggests two data clusters: high-income countries with low synchronicity and low-income countries with high synchronicity. This clustering suggests that per capita GDP might be proxying for another measure of economic development that also exhibits such clustering.

In summary, the R_j^2 and f_j measures of synchronicity behave similarly. Both measures show a clearly negative relation between stock price synchronicity and per capita income, with some evidence of clustering.

4. Empirical framework

What explains the highly significant negative correlation between stock price synchronicity and per capita GDP? Per capita GDP is a general measure of economic development. In this section, we hypothesize that particular economy characteristics, or dimensions of economic development, might plausibly be related to stock price synchronicity, and that per capita GDP might serve as a proxy for these characteristics. Our strategy is to see which development measures are most correlated with stock price synchronicity, and to ask whether they render per capita GDP insignificant in multivariate regressions. From this exercise, we hope to learn what economic linkages might underlie the correlation between stock price synchronicity and per capita income.

4.1 Stock price synchronicity dependent variables

Our two stock price synchronicity measures, f and R^2, are unsuitable as dependent variables in regressions because they are bounded within the intervals [0.5, 1] and [0, 1] respectively. We therefore adopt a standard econometric remedy and apply logistic transformations to these variables. Our left-hand side variables are thus

$$\text{Ø}_j = \log\left(\frac{f_j - .5}{1 - f_j}\right), \text{ and} \tag{8}$$

$$\tilde{\text{O}}_j = \log\left(\frac{R_j^2}{1 - R_j^2}\right). \tag{9}$$

In Eq. (8), Ψ_j maps f_j from the interval [0.5,1] to $\mathbb{R}$, the set of real numbers from negative to positive infinity. Similarly, in Eq. (9), $\tilde{\text{O}}_j$ maps R_j^2 from the unit interval to $\mathbb{R}$. The construction of R_j^2 and f_j are as described in Section 3. Both variables are based on 1995 data, though our results are similar if we use 1993 or 1994 data. Scatter plots (not shown) reveal that these transformations preserve the clustering effect noted above.

4.2 Controlling for stock market size

By construction, the co-movement measures, R^2 and f, decrease with the number of securities in a country's stock market. If the sign of the stock return is random, the Law of Large Numbers pushes f_j to approximately 0.5 as the number of stocks grows large. That is,

$$E[f_{jt}] = E\left[\frac{\max[n_{jt}^{up}, n_{jt}^{down}]}{n_{jt}^{up} + n_{jt}^{down}}\right] \cong \frac{1}{2}, \tag{10}$$

for a short window in which the expected return is close to zero. Also, the market index on the right-hand side of Eq. 6, which forms the basis for the construction of our R_f^2 price synchronicity variable, is a weighted average of the individual stock returns used as dependent variables. This construction produces a similar spurious correlation between number of securities listed and this price synchronicity variable. Intuitively, in a market with few securities, each individual security is a more important part of the market index. Thus, higher synchronicity might simply reflect fewer traded stocks.

To control for these effects, we use the logarithm of the number of listed stocks in 1995 in each stock market, taken from *Datastream*. However, a correlation between synchronicity and market size may also reflect better functioning stock markets having more listings. By controlling for number of listings, we may be introducing downward bias in the significance of variables that measure stock market quality.

4.3 Regression framework

In the following analysis, we propose hypotheses as to why certain economy characteristics might be related to stock price synchronicity. We construct a vector $\mathbf{x_j}$ measuring these characteristics, and include it in regressions of the form

$$\text{Õ}_j \text{ or } \text{Ø}_j = c_0 + c_1 \log y_j + c_2 \log n_j + \mathbf{c} \quad \mathbf{x_j} + u_j, \tag{11}$$

where Õ_j and Ø_j are our logistically transformed price synchronicity variables, y_j is per capita GDP, n_j is the number of listed stocks, and u_j is a random error term. Our objective is to see which characteristics $\mathbf{x_j}$ significantly explain stock price synchronicity and render the logarithm of per capita GDP insignificant.

5. Structural Explanations

In this section, we consider the hypothesis that the negative correlation between stock price co-movement and per capita income is due to firms in low-income economies having more correlated economic fundamentals. To test this hypothesis, we include specific structural variables in the vector $\mathbf{x_j}$ that might provide separate proxies for such an effect. These variables are macroeconomic volatility, country size, and economy diversification. Since these variables may not encompass all sources of market-wide price movement, we also include a direct measure of earnings co-movement for firms in each economy using standardized firm-level accounting data. If including these variables in the vector $\mathbf{x_j}$ renders per capita income insignificant in regression (11), we can conclude that per capita income provides a proxy for these structural effects.

A description of each structural independent variables follows.

5.1 Macroeconomic instability

Some economies could have unstable market fundamentals because of macro-economic instability. In these economies, volatile market fundamentals may overwhelm variations due to firm-specific factors, so that stock prices tend to move together. If so, our finding of greater stock price synchronicity could be attributed to macro-economic instability.

To measure macroeconomic instability, we use the variance of per capita GDP growth for each country, with per capita GDP measured in nominal U.S. dollars, estimated from 1990 to 1994. We use the variance of the domestic inflation rate across the same period as a robustness check.

5.2 Country size

Country size per se could matter in at least two ways.[3] First, economic activity in a small country could be geographically localized, so that nearby geopolitical instability or localized environmental catastrophes such as earthquake or monsoons might have market-wide effects that would not be as evident in a larger country. For example, Finland's economy shrank by 15% in the early 1990s as the neighboring Soviet Union disintegrated amid severe structural changes and Finland's role as a gateway to Russia temporarily lost value. Hong Kong's economy is similarly dependent on events in mainland China.

Second, Bernstein and Weinstein (1998) observe the economic specialization predicted by standard international trade theory across geographical units of similar size, but not across countries. This finding is consistent with larger countries having factor endowments that exhibit less uniformity, and this relation in turn suggests that the stocks of firms in large countries might move more independently than those in small countries. For example, if oil prices fall, the prospects of Ohio manufacturing firms brighten, while those of Texas oil companies dim, resulting in observable asynchronous stock price movements in the U.S. markets. In contrast, stocks in a smaller oil-producing country, like Venezuela, might move more synchronously as oil prices change, given that a larger position of Venezuelan economic activity is devoted to providing goods and services for oil companies and their employees. Similar stories might be told about the dependence of smaller countries on particular agricultural crops, mining operations, or industries.

To capture any relation between country size and synchronicity in stock returns, we use the logarithm of geographical size, in square kilometers, for each country. We use the logarithm of population in a robustness check.

5.3 Economic and managerial diversification

The second point above is closely related to economic specialization. In some economies, listed firms could be concentrated in a few industries. Consequently, the fundamentals of these firms could be highly correlated, and their stock prices highly synchronous. Undiversified economies should therefore exhibit more stock price synchronicity than diversified ones. If poor countries are relatively undiversified, this characteristic might explain our finding.

Alternatively, some economies may be dominated by a few very large firms. If most other listed firms are suppliers or customers of these dominant firms, a high degree of stock price synchronicity might ensue. Problems that would be firm-specific in a larger economy, such as leadership succession within a controlling family, can potentially affect the entire economy. If economies of poor countries depend disproportionately on a few large firms, our finding could follow.

To capture these effects, we construct an industry Herfindahl index and a firm Herfindahl index for each country. We define the industry Herfindahl index of country *j* as $H_j = \sum_k h_{k,j}^2$ where $h_{k,j}$ is the combined value of the sales of all country *j* firms in industry *k* as a percentage of those of all country *j* firms. Analogously, we define the firm Herfindahl index of country *j* to be $\hat{H}_j = \sum_i \hat{h}_{i\,j}^2$ where $\hat{h}_{i,j}$ is the sales of firm *i* as a percentage of the total sales of all country *j* firms. These indices are constructed using 1995 data and industry classifications from Datastream. The latter classifications are roughly equivalent to using 2-digit Standard Industrial Classification (SIC) codes to define industry categories. High values of the industry and firm Herfindahl indexes indicate respectively, a lack of industry diversity and the dominance of a few large firms r. Roll (1992) finds that high industry or high firm concentration, as captured by such Herfindahl indices, partly explains the high volatility of some stock market indices.

5.4 Synchronous fundamentals

Firm fundamentals might move together more in low-income countries for the above reasons, or for other reasons. For example, if highly diversified conglomerates account for a larger fraction of listed firms, their returns should all resemble the market return. Widespread intercorporate ownership might also cause firm fundamentals to move together, as intercorporate ownership implicitly causes the performance of some firms to depend on that of other firms. This effect is exacerbated if related firms use intercorporate transactions to assist each other in bad times or to share the bounty in good times. All such explanations posit a greater correlation across firms in economic fundamentals. A general measure of co-movement of firm fundamentals can therefore act as a comprehensive structural independent variable, capturing all of these various explanations.

To capture the general synchronicity of firm-level fundamentals, we construct an earnings co-movement index by running the regression

$$ROA_{i,j,} = a_i + b_{\mathrm{i}} \times ROA_{m,j}, \tag{12}$$

for each firm i in each country j. $ROA_{i,j}$ is a firm's returns on assets, calculated as annual after-tax profit plus depreciation over total assets. $ROA_{m,j}$ is the value-weighted average of the return on assets for all firms in the country.

Our firm-level earnings data contain isolated irregularities, appearing as single spikes in the data. These irregularities generally reflect extraordinary items in the calculation of firm earnings, and are treated as statistical noise for our purposes. To mitigate these data problems, we exclude $ROA_{i,j}$ in period t if ($ROA_{i,j,t}$ - $ROA_{i,j,t-1}$) and ($ROA_{i,j,t}$ - $ROA_{i,j,t+1}$) are opposite in sign and are both greater than 0.75 in absolute value.

Firm level accounting data are sparse for some countries, and completely unavailable in a few, especially prior to the mid-1990s. Using more years of data arguably allows better regression estimates, but also worsens the problem of obtaining comparable data for a statistically meaningful number of countries. We use five years of data from 1993 to 1997. Due to missing data, we can run such firm-level *ROA* regressions in only 24 countries. These countries are Australia, Austria, Belgium, Brazil, Chile, Denmark, Finland, France, Germany, Greece, Holland, India, Italy, Japan, Korea, Mexico, Norway, Portugal, Spain, Sweden, Taiwan, Turkey, the United Kingdom and the U.S. For three of these countries, Austria, Chile, and Taiwan, earnings data are available for very few firms. Dropping these three countries does not qualitatively affect our basic findings. To mitigate problems associated with the loss in sample size, we conduct our empirical investigation both with and without the earnings co-movement index.

After running these regressions on firm-level return on assets data for these countries, we then average the R^2s of these regressions to construct a weighted average earnings R^2 for each country. This calculation yields our earnings co-movement measure,

$$Earnings\ Co\text{-}movement\ Index = \frac{\sum_i R^2_{i,j}(ROA) \times SST_{i,j}(ROA)}{\sum_i SST_{i,j}(ROA)}. \tag{13}$$

Our earnings co-movement index is analogous to using the R^2 from Eq. (6) as a stock price synchronicity measure, but measures the synchronicity of firm fundamentals instead. We expect fundamentals synchronicity to be positively related to stock return synchronicity.

5.5 Stock price synchronicity and structural variables

Table 3 display univariate statistics and simple correlation coefficients for our stock price synchronicity variables, the logarithm of per capita GDP and the number of listed stocks, and the structural variables listed above. The logarithm of the number of listed stocks is negatively correlated with price synchronicity, as anticipated.

The signs of the correlations of stock price synchronicity with the structural variables are largely as expected. Price synchronicity is negatively correlated with a country's geographical size and positively correlated with both GDP growth variance and earnings co-movement, although these correlations are all statistically insignificant. More diversification is not consistently correlated with less stock price synchronicity. Overall, these correlations suggest that no one structural variable is likely to explain the link between per capita GDP and stock price synchronicity.

Panel B of Table 3 also shows that per capita GDP is significantly negatively correlated with a country's geographical size, and essentially uncorrelated with diversification. Clearly, our basic result cannot be due to low-income countries being small and undiversified.

Table 4 displays multivariate regressions of the form of regression (11), to see if the structural variables, acting in concert, might explain the link between per capita GDP and stock price synchronicity. First, note that a small country effect appears in this multivariate setting. Stock prices do move together more in smaller countries. However, this effect does not explain the correlation between price synchronicity and per capita GDP, as that variable remains highly significant. This result suggests that per capita GDP does not serve as a proxy for our structural variables, taken either separately or all together, and that factors beyond our structural explanations underlie the negative relation between per capita GDP and stock price synchronicity.

5.6 Robustness checks

Some clarifications are in order. First, we can never categorically reject the structural hypothesis using regressions like the alternative specifications defined above. Additional structural variables can always be found, and some combination of these variables may explain price synchronicity, rendering per capita GDP insignificant. Second, our structural variables may be noisy. Third, earnings co-movement is not necessarily successful in capturing the co-movement of fundamentals, as stock prices are thought to be based on expected future cash flow, not current earnings. The relation of price fundamentals to variables based on accounting numbers, as well as to historical macroeconomic variables, can be complicated.

Since we run country-level cross-sectional regressions, our sample size is limited. As we add variables to our model, the available degrees of freedom are exhausted quickly. Our robustness tests therefore consist of statistical fit tests, replacing structural variables with alternatives or adding only a small number of additional variables at a time.

5.6.1 Outliers

Our regression results are not driven by outliers. We conduct diagnostic checks on the residuals obtained in Table 4. We find no outliers using *Student R* and *Cook's D* measures.

5.6.2 Time period effects

One way to check whether our results are due to transitory time effects is to repeat our regressions using data taken from other years. We can only repeat the regressions using 1993 and 1994 data because of missing data problems in Datastream for earlier years. We obtain identical conclusions using the two earlier years.

The major transitory event in 1995 was the aftermath of the depreciation of the Mexican Peso. This major macroeconomic event could have driven up the synchronicity of stock prices in Latin American countries. We repeated our regressions dropping all Latin American countries in our sample. Our results are not qualitatively affected.

5.6.3 Alternate stock return synchronicity measures

Our stock return synchronicity indexes are necessarily arbitrary. However, our stock price synchronicity measures, both $Õ_j$ and $Ø_j$, give qualitatively similar results, despite substantial differences in their construction. In estimating R_j^2 statistics for stock return regressions, we incorporate the possibility that stock prices in other economies are influenced by the U.S. market. If some stock markets are isolated, adding the U.S. market return should not affect their R_j^2 regression statistics. The R_j^2 statistic for the U.S. is constructed without allowing for the influence of foreign markets on U.S. stock prices. This construction could create a downward bias in the estimated U.S. R^2. However, our results are qualitatively unchanged if we drop the U.S. from our sample.

As further robustness checks, we consider several alternative measures of stock return synchronicity. The first is the average simple correlation across pairs of stocks, $\frac{1}{2(n-1)^2}\sum_{i=1}^{n}\sum_{k\neq i} r_{ik}$. The second is the average squared simple correlation, $\frac{1}{2(n-1)^2}\sum_{i=1}^{n}\sum_{k\neq i} r_{ik}^2$. The number of pair-wise combinations rises with the square of the number of listed stocks, n. Computation becomes difficult for $n > 150$. We therefore randomly choose 50 stocks from each country and calculate the average of the 2,450, or n^2 - n, resulting pair-wise simple correlation coefficients. Another alternative measure is the fraction of pairs in which the average simple correlation coefficient is above a certain threshold, as given by

$$\frac{1}{2(n-1)^2}\sum_{i=1}^{n}\sum_{k\neq i}\delta_{ik} , \qquad (14)$$

where δ_{ik} is one if ρ_{ik} is above $\hat{r}$, and is zero otherwise. We consider $\hat{r}$ equal to 50%, 40%, 30%, and 20%.

All of these alternative synchronicity measures generate qualitatively similar results to the measures used in the text, but at generally lower levels of statistical significance. Average correlation coefficients generate less significant results than both average squared correlation coefficients and the fraction of correlations above threshold values of $\hat{r}$. For the last calculation, a 50% cutoff generates results with statistical significance similar to the reported results.

5.6.4 Alternative methods of controlling for market size effects

By construction, the synchronicity indices are affected by the number of stocks in a market. We control for this market size effect by explicitly introducing the logarithm of the number of listed stocks as an independent variable. Another way to overcome this effect is to constrain the number of stocks we use to construct our synchronicity indices. The alternative synchronicity measures discussed in the previous section are based on 50 stocks from each country, and so are unaffected by such problems. Yet they generate qualitatively similar results to those shown. We can also reproduce our results using a restricted number of stocks in each country to construct our stock price synchronicity variables, $\tilde{O}_j$ and $Ø_j$. The median number of listings in the stock markets in our sample is 300. For countries with fewer than 300 stocks, we use all stocks to construct the information content measures. For countries with more than 300 stocks, we randomly select 300 stocks. We then re-estimate the test shown in Table 4 twenty times, using 300 different randomly drawn firms each time and indexes based only on those firms. In every run, the results are qualitatively identical to those reported.

5.6.5 Unstable monetary policies

If the stock markets in low-income countries are volatile because of swings in monetary policy, the variance in the inflation rate might be a better variable than the variance of GDP growth for explaining stock price synchronicity. This variable, like GDP growth variance, enters our equation with the predicted sign, but is even more insignificant than the variable it replaces.

5.6.6 Alternative measure of country size

In Table 4, we measure country size by the logarithm of the area of each country in square kilometers. This metric makes sense if extreme weather or other localized natural phenomena cause synchronicity in stock prices. However, geographical area is only one measure of country size, and population is an obvious alternative country size metric. Substituting the logarithm of population does not change our findings.

5.6.7 Commodity-based economies

If poor countries are disproportionately dependent on raw materials production, and these industries are more pro-cyclical than others, our basic finding might follow. Including a dummy variable which equals one if raw materials are the country's most important sector, and zero otherwise, also changes nothing in our reported results. This structural hypothesis is also apparently not responsible for our basic finding.

Because our focus is on the stock market data, our sample excludes very small and very poor countries, as such countries generally have no stock markets. We thus are neither proving nor disproving the idea that dependence on undiversified raw materials production might cause economy-wide fluctuations in such economies.

5.6.8 Alternative measures of fundamentals co-movement

Our earnings co-movement variable could be a noisy measure of fundamentals comovement. Using many years of historical data makes the variable too dependent on the past, which is likely inappropriate for fast-changing economies. On the other hand, using too few years of data makes it difficult to estimate the variable precisely. The earnings co-movement measure is estimated using five years of annual data. We experimented with six and seven years of data instead. Both alternatives generate qualitatively similar results to those reported. We use ROA market indices that are weighted by asset values. Using equally weighted indices also leads to similar findings. Applying a logistic transformation also generates qualitatively similar results.

As another measure of disparity in firm fundamentals, we use the cross-sectional variance of firm ROA in each country. We average these cross-sectional variances over 1992, 1993, and 1994. Using this variable does not change our results.

In conclusion, after treating an exhaustive list of robustness concerns, we find that our results remain intact.

6. An Institutional development explanation

In the previous section, we showed that including structural variables in the vector $\mathbf{x_j}$ does not render per capita income insignificant in the regression in Eq. (11), and argued that per capita income is not proxying for structural effects. In this section, we consider a second general hypothesis, that the negative correlation between stock price co-movement and per capita income is due to low-income economies providing poor protection of private property rights.

We construct a a good government index to measure how well country *j* protects private property rights. We denote this index g_j, and include it in regressions of the form

$$\tilde{O}_j \text{ or } \text{Ø}_j = c_0 + c_1 \log y_j + c_2 \log n_j + \mathbf{c} \quad \mathbf{x_j} + c_3\, g_j + u_j, \tag{15}$$

where $\tilde{O}_j$ and Ø_j are our logistically transformed price synchronicity variables, y_j is per capita GDP, n_j is the number of listed stocks, $\boldsymbol{x_j}$ is a vector of economy structural characteristics, and u_j is a random error term. If the good government index is significant, and including it renders per capita GDP insignificant, we have evidence that a lack of property rights protection underlies the high degree of stock price synchronicity.

6.1 Why property rights protection might affect stock price movements

In many countries, governments and courts are mercantilist devices for diverting wealth to an entrenched elite. Politicians can "shut down [a] business, kick it out of its premises, or even refuse to allow it to start" (Shleifer, 1994) by using a variety of tactics including open legislation, licensing requirements, repudiation of commitments, and nationalization. Asset values are predominantly affected by political connections and events. For example, Fisman (1999) estimates that as much as 25% of the market value of many Indonesian firms is related to political connections based on stock price movements in response to rumors about President Suharto's health. In such countries, political events, or even rumors about political events, could cause large market-wide stock price swings and generate high levels of stock price synchronicity.

Thus, stock price synchronicity might reflect higher political risk. However, it is important to recall that stock price synchronicity is not explained above by macroeconomic volatility or synchronous economic fundamentals.

If our structural variables are adequate, political risk must affect share prices through some other channel. Admittedly, our structural measures could be flawed. For example, investors might expect systematic fluctuations in future fundamentals to arise from current political events. Such politically sensitive growth options in low-income countries might explain how their highly synchronous stock returns can be unrelated to synchronicity in past earnings . We invite further work to explore these possibilities.

However, bad government might increase stock price synchronicity through channels that are not directly associated with economic fundamentals. Finance theory posits that risk arbitrageurs expend resources uncovering proprietary information about stocks and earn an acceptable return by using that information to trade against less informed investors. Risk arbitrageurs accumulate information until the marginal cost of gathering an additional unit of information exceeds its risk-adjusted marginal return. Such trading by many risk arbitrageurs, each with unique proprietary information, is thought to capitalize information into share prices (Grossman, 1976; Shleifer and

Vishny, 1997). Risk arbitrage, of this sort may be less economically attractive in countries that protect private property rights more poorly for several reasons.

First, economic fundamentals may be obscured by political factors in many low-income countries. Second, political events may be hard to forecast in low-income countries, whose governments are often relatively opaque and erratic. Third, risk arbitrageurs who do make correct predictions may not be allowed to keep their earnings in countries that protect private property rights poorly, especially if the risk arbitrageurs are political outsiders. Because of these factors, firm-specific risk arbitrage could be relatively unattractive in countries that protect private property rights poorly, and informed trading correspondingly thin.

If weak property rights discourage informed risk arbitrage, they might also create systematic stock price fluctuations. De Long et al. (1990) argue that insufficient informed trading can "create space" for noise trading. Indeed, what De Long et al. (1990) call a "create space" effect is central to their model of systematic noise trader risk. They define this effect as follows: "As the variability of noise traders' beliefs increases, the price of risk increases. To take advantage of noise traders' misperceptions, sophisticated investors must bear this greater risk. Since sophisticated investors are risk averse, they reduce the extent to which they bet against noise traders in response to this increased risk." [De Long, et al. (1990, 715)]. If the proportion of noise traders in the market is above a critical level, this effect causes noise trading to grow in importance relative to informed trading, and eventually "dominate the market" (ibid., 720).

Thus, De Long et al. (1989, 1990) argue that stock markets without a sufficient amount of informed trading could be characterized by large systematic price swings due to noise trading. If the governments of low-income countries do not respect property rights and thereby discourage informed trading in their stock markets, share prices in those markets scould exhibit intensified market-wide variation and high synchronicity.

6.2 Measuring good government

To capture the extent to which a country's politicians respect private property rights, we construct a good government index as the sum of three indexes from La Porta et al. (1998b), each ranging from zero to ten. These indexes measure (i) government corruption, (ii) the risk of expropriation of private property by the government, and (iii) the risk of the government repudiating contracts. Low values for each index indicate less respect for private property.

La Porta et al. (1998b) describe these three indexes as follows: The "corruption index" is an assessment of corruption in government by the International Country Risk Guide (ICR). Low scores of this index indicate that "high government officials are likely to demand special payments" and that "illegal payments are generally expected throughout lower levels of government" in the form of "bribes connected with import and export licences, exchange controls, tax assessment, policy protection, or loans." The "risk of expropriation index" is the ICR's assessment of the risk of "outright confiscation" or "forced nationalization." The "repudiation of contracts by government index" is ICR's assessment of the risk of a "modification in a contract taking the form of a repudiation, postponement, or scaling down" due to "budget cutbacks, indigenization pressure, a change in government, or a change in government economic and social priorities." All three ICR indexes are averages of the monthly indexes for April and October from 1982 to 1995. The good government index, like our synchronicity measures, tends to be quite high for developed countries and quite low for emerging economies.

6.3 *The relation of stock price synchronicity to good government*

The good government index is available for all countries except China, the Czech Republic, and Poland. Tables 3 reports univariate statistics for our good government index, as well as its simple correlations with the stock price synchronicity indices, Õ$_j$ and Ø$_j$, per capita income, market size, and the structural variables.

The pattern of the simple correlation coefficients in Panel A of Table 3 is consistent with the view that better protection of private property rights reduces stock price synchronicity. In addition, Panel B shows that countries with higher per capita income have higher good government indices. It also shows that the good government index is significantly correlated with market size, measured as the logarithm of the number of stock in the country's stock market, a finding that is consistent with more institutionally advanced economies having markets on which more stocks trade. This result confirms our premise that including market size as a control variable biases our tests against finding that institutional development matters.

The regressions in Table 5 show that the good government index remains significantly negatively correlated with stock price synchronicity after controlling for market size and the structural variables. More important, the logarithm of per capita GDP becomes insignificant in regressions containing the good government index.

In summary, our results in this section are consistent with the view that a greater respect for private property rights by governments in developed economies underlies our finding that stock prices in high-income countries are less synchronous than in low-income countries.

6.4 More market-wide variation or less firm-specific variation?

Our stock return synchronicity measure Õ$_j$ can be decomposed into market wide variation and firm specific variation. Õ$_j$ is the logistic transformation of the R_j^2 in Eq. (7), which can be written as

$$R_j^2 = \frac{\sum_{i\in j} R_{i,j}^2 SST_{i,j}}{\sum_{i\in j} SST_{i,j}} = \frac{\sum_{i\in j} \frac{\sigma^2_{m,i,j}}{\sigma^2_{\varepsilon,i,j}+\sigma^2_{m,i,j}}\left(\sigma^2_{m,i,j}+\sigma^2_{\varepsilon,i,j}\right)}{\sum_{i\in j}\left(\sigma^2_{m,i,j}+\sigma^2_{\varepsilon,i,j}\right)}, \tag{16}$$

where $\sigma^2_{m,i,j}$ is the variation in the return of firm *i* in country *j* explained by market factors and $\sigma^2_{\varepsilon,i,j}$ is the residual variation in firm *i*'s return. Substituting Eq. (16) into the definition of Õ$_j$ yields

$$Õ_j = \log\left(\frac{\sigma^2_{m,j}}{\sigma^2_{\varepsilon,j}}\right) = \log\left(\sigma^2_{m,j}\right) - \log\left(\sigma^2_{\varepsilon,j}\right), \tag{17}$$

where the average variation in country *j* stock returns that is explained by market factors is $\sigma^2_{mj} = \frac{1}{n}\sum_i \sigma^2_{i,j,m}$, and $\sigma^2_{\varepsilon j} = \frac{1}{n}\sum_i \sigma^2_{i,j,\varepsilon}$ is the average firm-specific variation in country *j* stock returns.

If noise trader risk makes stock prices more synchronous in countries with weak private property rights, we should find Õ$_j$ to be high in those countries because of high market-wide stock price variation, ó$^2_{m,j}$. If higher synchronicity in emerging markets is due to less firm-specific variation, ó$^2_{å,j}$, other explanations must be sought.

Figure 6 explores this issue by displaying the average firm-specific variation, ó$^2_{å}$, and market-wide variation, σ_m^2, in U.S. stock returns from 1926 to 1995. Each bar represents a 3-year average. The decreases in R^2s in the post-war period appear to be associated with both the capitalization of more firm-specific information into stock prices and with a decline in the influence of market-wide factors.

Since a high R^2 can reflect low levels of firm-specific variation, $\sigma_{\varepsilon,j}^2$, or high levels of market-wide variation, $\sigma_{m,j}^2$, or both, it is useful to relate these measures. Table 6 reveals $\sigma_{\varepsilon,j}^2$ to be greater than $\sigma_{m,j}^2$ in all countries except Poland. Figure 7 shows that the greater synchronicity exhibited in emerging markets is associated with greater systematic stock return variation, $\sigma_{m,j}^2$, and with no clear pattern of higher or lower firm-specific return variation, $\sigma_{\varepsilon,j}^2$. In contrast, lower synchronicity within developed economies is associated with lower $\sigma_{\varepsilon,j}^2$, and with $\sigma_{m,j}^2$ at a relatively uniform low level.

Panel A of Table 3 shows the simple correlations of $\log(\sigma_{\varepsilon,j}^2)$ and $\log(\sigma_{m,j}^2)$ with our other country-level cross-section variables. Stock price synchronicity is positively correlated with high market risk, but not with low firm-specific risk. Both per capita GDP and the good government index are negatively correlated with $\log(\sigma_{\varepsilon,j}^2)$ and $\log(\sigma_{m,j}^2)$ and, in both cases, the correlations with systematic risk are stronger and more significant.

To test the hypothesis that increased synchronicity is primarily due to increased market-wide price variation, Table 7 considers regressions of the forms

$$\log(\sigma_{\varepsilon,j}^2) = c_0 + c_1 \log y_j + c_2 \log n_j + \mathbf{c}\ \ \mathbf{x_j} + c_3\, g_j + u_j, \text{ and} \tag{18}$$

$$\log(\sigma_{m,j}^2) = c_0 + c_1 \log y_j + c_2 \log n_j + \mathbf{c}\ \ \mathbf{x_j} + c_3\, g_j + u_j, \tag{19}$$

where $\boldsymbol{x_j}$ is a vector of structural and institutional development variables, y_j is per capita GDP, n_j is the number of listed stocks, g_j is the good government index, and u_j is a random error term.

Table 7 shows the good government index to be negatively and significantly related to market-wide stock price variation. The good government index is also negatively related to firm-specific stock price variation, but this effect is smaller in magnitude and, at best, significant only in a one-tailed test, as seen in column 3 of Table 7. Although Figures 6 and 7 are more ambiguous, Tables 3 and 7 are broadly consistent with the conjecture that noise trading generates market-wide stock price fluctuations unrelated to fundamentals movements in economies with uncertain private property rights.

6.5 More robustness checks

The results in Tables 5 and 7 survive all the same robustness checks discussed above in connection with Table 4. The results are not due to outliers, transitory effects, particular synchronicity measures, different sized markets, monetary instability, commodity dependence, fundamentals co-movement, or fundamentals volatility.

In principle, it would be desirable to add more institutional variables. However, this exercise is impractical given our limited sample size, and because other measures of institutional development tend to be highly correlated with the good government index. We therefore replace the good government index with other measures of property rights protection, testing each alternative measure in turn.

The alternative property rights measures we use are a rule of law index and a judicial efficiency index, both described in detail in La Porta et al. (1998a). Both measures generate qualitatively similar results to those shown for the good government index.

The size of a country's stock market may be a function of its institutional maturity. We already include the logarithm of the number of listed stocks. Adding stock market capitalization or its logarithm as an additional variable does not qualitatively change our results.

6.6 Two stock market regimes?

We have remarked above that Figure 5, which displays scatter plots of stock price synchronicity versus income, shows two clusters: high-income countries with low stock price synchronicity and low-income countries with high synchronicity.[4] The regressions in Table 5 show that the good government index captures this dichotomy better than per capita income does. Indeed, replacing the logarithm of per capita GDP in Figure 5 with the good government index again clearly reveals two clusters.

This clustering suggests the possibility of a threshold effect. If institutional development, as measured by our good government index, is below a critical level, a different regime governs stock prices, and a high degree of synchronicity is observed. Marginal changes that do not cross this threshold might have little effect.

To test whether our results hold within both subsamples or mainly describe differences between the two subsamples, we repeat the correlations and regressions in our tables separately on subsamples of high and low good government index countries. We use the mean of the good government index (23.92) as the dividing line in creating these subsamples, yielding a developed economy subsample of 22 countries, and an emerging economy subsample containing 15 countries. Minor changes in the dividing line do not affect our results. Note that dividing the sample into the two clusters shown in Figure 5, countries with a logarithm of per *capita* GDP above and below nine, generates precisely the same partition. Dividing the sample according to whether the "rule of law index," introduced in the previous subsection, is above and below its average also generates precisely the same partition.

In emerging economies, the analogues of Tables 3 and 5 (not shown) reveal stock market synchronicity to be correlated with neither the logarithm of per capita GDP nor the good government index. In the analogue of Table 5, both variables remain uncorrelated with synchronicity. Overall, synchronicity in the emerging markets appears unrelated to marginal changes in the protection accorded private property. This result is consistent with the existence of a threshold level of institutional development associated with relatively asynchronous stock pricing.

In the developed country subsample, the situation is more complex. As in emerging markets, synchronicity is unrelated to per capita GDP. But within developed countries, synchronicity is higher when the good government index is lower in the analogues of Tables 3 and 5, though this effect is significant only in one-tailed tests. Moreover, high synchronicity in developed countries is associated both with low levels of firm-specific variation, σ_ε^2, and high levels of market-wide variation, σ_m^2. This result is consistent with the U.S. data shown in Figure 6. This finding motivates a closer look at the developed countries to clarify the determinants of stock price synchronicity there.

7. More capitalization of firm-specific information in high-income countries?

In this section, we consider two variants of the hypothesis that a country's institutions might affect the relative amounts firm-specific versus market-wide information that are capitalized into stock prices set by rationally informed risk arbitrageurs. First, we test the hypothesis that firm-specific risk arbitrage is more attractive in economies that force firms to provide better accounting data. Second, we test the hypothesis that firm-specific risk arbitrage is more attractive in economies that provide better protection for public investors from corporate insiders. We motivate both hypotheses in more detail below.

We conduct our tests on the emerging economy subsample of countries with below average good government indexes, on the developed economy subsample of countries with above average good government indexes, and on the full sample. We repeat the tests for these three groups because accounting rules and investor rights laws might be dead letters in countries with weak institutions. Since accounting rules and public investor protection require the rule of law, the two hypotheses introduced above might be relevant primarily in the developed country subsample.

7.1 The importance of proprietary firm-specific information in the United States

Recall from Eq. (17) that high stock return synchronicity can be due to either high systematic variation, or low firm-specific variation, or both. Figure 7 reveals that both systematic and firm-specific return variation differ substantially across countries. In emerging economies, higher stock price synchronicity is mainly associated with greater systematic variation, $\sigma^2_{m,j}$; but in developed economies, lower synchronicity is also associated with greater firm-specific variation, $\sigma^2_{\varepsilon,j}$.

Roll (1988) and French and Roll (1986) stress the importance of proprietary firm-specific information, which they propose is reflected by σ^2_{ε}, in U.S. stock prices. Roll (1988) considers cross-sectional average R^2 measures comparable to Eq. (7) as measures of the explanatory power of asset pricing models. Using 1982 to 1987 data, he finds low R^2s of about 35% with monthly data and about 20% with daily data, and concludes that asset pricing models have very limited explanatory power. Pointing out that stock price changes reflect unpredictable industry and firm-specific factors as well as systematic factors, he drops observations for dates when news about a firm, or its industry, is reported in the financial press. This refinement improves his R^2s only slightly. French and Roll (1986) find U.S. stock returns to be more volatile during exchange trading hours than during non-trading hours, and argue that private information is the principle factor behind high trading-time variance.

French and Roll (1986) and Roll (1988) both conclude that most of the variation in U.S. stock prices reflects the capitalization of proprietary firm-specific information. These results raise the possibility that low levels of synchronicity in some country's stock prices might reflect the incorporation of more firm-specific information into prices in their stock markets.

7.2 Firm-level accounting data and stock price synchronicity in developed economies

If accounting data are more useful, more firm-specific public information is available to all investors. This plausibly lets risk arbitrageurs make more precise predictions regarding firm-specific stock price movements. Thus, we might observe more firm-specific price variation in countries with better accounting standards.

To test this hypothesis, we rerun the correlations and regressions in Tables 5 and 7, for both the full sample and the emerging and developed economy subsamples separately, using a direct measure of the sophistication of each country's accounting standards in place of our good government index. We take this variable from La Porta et al. (1998a), who construct the measure using 1990 data from *International Accounting and Auditing Trends, Center for International Financial Analysis and Research, Inc.* La Porta et al. (1998a) describe the construction of the accounting standards index as follows: "This index was created by examining and rating companies' 1990 annual reports on their inclusion or omission of 90 items. These fall into seven categories (general information, income statements, balance sheets, funds flow statement, accounting standards, stock data and special items). A minimum of 3 companies in each country were studied. The companies represent a cross section of various industry groups where industrial companies numbered 70 percent while financial companies represented the remaining 30 percent." They obtain annual reports from Moody's International, CIFAR, EXTEL, WorldScope, 20-Fs, Price Waterhouse and various country sources. The accounting standards index ranges from 36 to 83, with a high value indicating more detailed and useful disclosure requirements.

Univariate statistics for the accounting standards variable and its simple correlation coefficients with our other variables are shown in Table 3. Accounting standards are negatively correlated with synchronicity, but the significance levels are in the neighborhood of 20% indicating only a marginal relation between the variables, even in one-tailed tests. In regressions analogous to those in Tables 5 and 7 for both the full sample and the emerging and developed economy subsamples, substituting the accounting standards variable for the good government index produces results similar to those in Table 4. The accounting standards index itself is uniformly statistically insignificant. Adding the accounting standards measure as an additional explanatory variable also leaves it statistically insignificant, and does not affect the magnitude or significance of the good government index in the whole sample or either subsample. We conclude that either this effect is unimportant in explaining our findings, or our measure of accounting standards is flawed.

7.3 Differential capitalization of firm-specific and market-wide information?

A lack of respect for the property rights of public investors by controlling shareholders might impede the capitalization of firm-level information in stock prices in some developed countries. This hypothesis is motivated by the observation, noted above, that greater stock price synchronicity is associated with lower firm-specific returns variation among developed country stock markets.

This observation requires explanation. We conjecture that firm-specific risk arbitrage could be less cost effective in economies that more poorly protect public investors from insiders. If less firm-specific risk arbitrage therefore occurs, and Roll (1988) and French and Roll (1986) are correct in arguing that such risk arbitrage is the primary cause of firm-specific share price movements, we should observe lower firm-specific share price variation in such economies.

At this point we can only speculate about the underlying mechanism that might discourage firm-specific risk arbitrage in economies that fail to protect public investors from insiders. One possibility follows from the finding of La Porta et al. (1999), that control pyramids are the most common device insiders use to control public firms outside the United States. In a control pyramid, a family controls one firm, which holds controlling blocks of other firms, each of which holds controlling blocks in yet more firms, and so on. Such pyramids can have a dozen or more layers. Minority shares in some or all of these firms are traded publicly. Daniels and Morck (1994) stress that in Canada, where many publicly traded stocks are minority shares in firms in such control pyramids, the most important corporate governance laws are "oppression remedies," which stop controlling shareholders from shifting income between controlled firms through non-arm's-length transactions for goods, services, or capital at artificial prices. The problem is a type of insider trading, but is also akin to transfer pricing in multinational firms. In economies with control pyramids, weaker protection for public investors might render such income shifting more routine.

If income shifting involved strong firms subsidizing weak firms, firm fundamentals would become more correlated. If other criteria, such as each firm's relevance to the wealth, pet projects, status, or political influence of insiders, governed income shifting decisions, fundamentals correlation need not rise. Although the former sort of income shifting may happen in situations of financial distress, we postulate that the latter sort is more commonplace.

Shifting away abnormal profits that arise from market-wide factors attracts attention unless all other firms do likewise. In contrast, shifting firm-specific abnormal profits away requires no such concurrent action. Rational risk arbitrageurs, knowing they cannot predict where firm-specific abnormal profits will come to rest, should thus invest fewer resources in predicting firm-specific abnormal profits, and focus on market-wide plays. Such a focus implies that less firm-specific information should enter stock prices in economies where income shifting is easier. Stock return synchronicity should rise as firm-specific return variation falls in economies with poorer investor protection.

At least partly consistent with this mechanism, Bhattacharya et al. (2000) find that Mexican stock prices, return volatilities, trading volumes, and spreads simply do not respond to many types of firm-specific news that are known to affect U.S. stock prices. Although Bhattacharya et al. (2000) present evidence of insider trading to explain their finding, this evidence does not exclude the possibility that insiders appropriating firm-specific profits might limit firm-specific stock price movements. However, we admit the conjectural nature of this mechanism, and welcome alternatives explanations of why low firm-specific returns variation is associated with higher synchronicity in developed economies.

To test the more basic hypothesis that poor investor protection is associated with a reduced capitalization of firm-specific information, we rerun the regressions in Table 5 using a direct measure of the extent to which public shareholders' property is protected from appropriation by corporate insiders, anti-director rights index. This index is a score card of shareholders' rights against directors in various countries compiled by La Porta et al. (1998a). The measure can range from zero to six according to whether or not shareholders (i) can vote by mail, (ii) are barred from selling stock a few days prior to a shareholder meeting, (iii) can use cumulative voting for directors, (iv) have legal standing to sue directors or to force the company to buy back their shares, (v) have preemptive rights to new issues, and (vi) call extraordinary shareholder meetings relatively easily. Higher scores indicate that corporate insiders are more accountable to shareholders. Univariate statistics of the anti-director rights index and its simple correlation coefficients to our other variables are shown in Table 3.

La Porta et al. (1998a) emphasize that, for such rights to provide effective protection, a country must have functional political and legal systems. It is therefore plausible that the anti-director rights index might be most relevant in countries with good government, where the rule of law prevails. La Porta et al. (1998a) show that many countries, including some with strong property rights protection in general, poorly protect the property rights of public investors. This finding suggests that there might be enough variation in anti-director rights within our developed country subsample for statistical tests.

We therefore ran regressions like those in Table 5, but substituting the anti-director rights index for the good government index. We run these regressions for the whole sample and the developed and emerging economy subsamples. The anti-director rights index is insignificant in the whole sample and emerging economy subsample, but negative and highly statistically significant in the developed economy subsample. Recall that the good government index is also significant in the developed economy subsample. However, if both the antidirector rights and good government indexes are included in regressions using the developed country sub-sample, the good government index is insignificant.

If more firm-specific information is capitalized into stock prices in developed economies, decreased synchronicity in that subsample should be related to higher levels of firm-specific variation. Table 8 tests this hypothesis by running regressions analogous to those in Table 7, but either replacing the good government index with the anti-director rights index or including both. These regressions are run using only the developed economy subsample. Table 8 shows significantly more firm-specific price variation in stocks in developed countries that provide better protection of public shareholders against corporate insiders.

7.4 Additional robustness tests

We replicated the regressions in Table 8 replacing the antidirector rights interaction variable with a dummy variable for the origin of the country's legal system. La Porta et al. (1998a) show that countries with legal systems derived from those of France or Germany give public shareholders little protection against insiders. Thus, we thus set our legal origin dummy to zero if a country's legal system is modeled on that of France or Germany, and to one if it is modeled on those of Britain or Scandinavia. The results are qualitatively similar, and significance levels are similar to those for the anti-director rights variable. Regressions including the fundamentals correlation measure yield qualitatively similar results. In summary, we cannot reject the hypothesis that less firm-specific information is capitalized into stock prices in developed economies that provide less protection of public shareholders' property rights from corporate insiders.

8. Conclusions

We present empirical evidence that stock returns are more synchronous in emerging economies than in developed economies. We show that this result is not an artifact of structural characteristics of economies, such as market size, fundamentals volatility, country size, economy diversification, or the co-movement of firm-level fundamentals. Though some of these factors contribute to stock return synchronicity, a large residual effect remains, and this effect is correlated with measures of institutional development.

In particular, less respect for private property by government is associated with more market-wide stock price variation, and therefore also with more synchronous stock price movements. Since these market-wide price fluctuations are uncorrelated with fundamentals, we conjecture that poor property rights protection might deter risk arbitrage and, in the words of De Long et al. (1990), "create space" for noise traders. However, since we may be controlling for fundamentals volatility imperfectly, we cannot rule out other possible explanations.

We also show that, in developed economies, providing public shareholders with stronger legal protection against corporate insiders is associated with lower synchronicity. We conjecture that economies that protect public investors' property rights might discourage intercorporate income-shifting by controlling shareholders. Better property rights protection thus might render firm-specific risk-arbitrage more attractive in the stock markets of such economies.

Overall, our results suggest that stock markets in emerging economies may be less useful as processors of economic information than stock markets in advanced economies. The function of an efficient stock market is to process information, and thereby guide capital towards its best economic use. If stock price movements in emerging economies are mainly due to either politically driven shifts in property rights or noise trading, numb invisible hands in their stock markets may allocate capital poorly, thereby retarding economic growth. Consistent with this interpretation, Wurgler (2000) finds a higher elasticity of capital expenditure with respect to value added in countries whose stock returns are less synchronous, as measured in this study.

Finally, we recognize that these interpretations, though supported to some extent by our findings, remain conjectures. We invite alternative explanations of our econometric findings.

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Table 1. Stock price comovement in selected emerging and developed stock markets.
The fraction of stocks whose prices go up, go down, and remain the same during each of the first 26 weeks of 1995. Price changes are from Datastream, and are adjusted for dividends.

	CHINA			MALAYSIA			POLAND			Denmark			Ireland			United States		
Week	%Up	%Down	%Same	%Up	%Down	%Same	%Up	%Down	%Same	%Up	%Down	%Same	%Up	%Down	%Same	%Up	%Down	%Same
1	32	61	7	18	73	9	97	3	0	50	29	21	39	46	16	47	29	24
2	4	89	6	8	86	6	5	95	0	45	25	30	33	32	35	47	38	15
3	6	88	7	22	69	9	59	31	10	36	33	31	32	40	28	49	37	13
4	7	88	5	1	95	3	3	92	5	27	36	37	33	32	35	54	32	14
5	84	8	7	80	11	9	3	97	0	48	33	18	44	26	30	33	53	15
6	7	50	42	92	2	6	100	0	0	41	30	29	42	39	19	44	43	14
7	59	31	10	77	14	10	15	77	8	41	30	28	42	40	18	57	30	13
8	18	73	9	47	39	13	10	90	0	29	35	36	28	35	37	48	38	14
9	71	22	7	28	60	12	82	13	5	40	33	27	37	42	21	42	43	15
10	93	4	4	13	77	11	95	5	0	23	36	41	25	30	46	44	42	14
11	9	88	3	12	78	9	3	95	3	31	38	31	26	39	35	33	52	15
12	41	51	7	66	23	11	0	92	8	30	37	33	28	39	33	50	37	13
13	89	7	4	53	34	13	15	67	18	21	36	42	35	39	26	41	44	15
14	84	9	6	41	50	8	100	0	0	28	37	35	32	44	25	50	35	15
15	21	73	5	15	73	12	100	0	0	27	43	30	33	39	28	47	37	15
16	18	75	7	23	66	11	56	38	5	30	52	18	28	46	26	45	40	15
17	29	63	8	56	25	19	90	10	0	34	40	26	42	37	21	41	44	15
18	5	92	3	6	87	6	8	92	0	48	33	18	47	37	16	50	35	15
19	35	56	9	33	57	10	41	49	10	39	36	26	35	44	21	46	40	14
20	29	60	11	94	3	3	87	10	3	41	36	22	40	35	25	49	37	14
21	89	8	3	21	72	7	0	100	0	39	35	26	46	37	18	42	44	14
22	21	76	4	51	42	7	92	5	3	38	33	29	40	44	16	46	39	15
23	16	79	5	78	17	5	74	23	3	34	40	26	49	44	07	47	39	14
24	55	37	8	16	77	7	36	51	13	24	40	36	40	33	26	44	41	15
25	4	84	12	72	18	9	41	49	10	22	41	37	49	33	18	52	34	14
26	73	20	7	30	60	9	82	5	13	26	40	34	39	49	12	47	39	14
sample	308 stocks			349 stocks			38 stocks			233 stocks			57 stocks			6,889 stocks		

Table 2: Per capital gross domestic product and stock return synchronicity
Countries are ranked by per capita GDP in Panel A. In panel B, countries are ranked by stock return synchronicity, measured by the fraction of stocks moving together in the average week of 1995. In panel C, countries are ranked by stock market synchronicity, measured as the average R^2 of firm-level regressions of bi-weekly stock returns on local and U.S. market indexes in each country in 1995. Returns include dividends and are trimmed at ±25%.

Panel A			Panel B		Panel C	
country	number of listed stocks	1995 per capita US$ GDP	country	% stocks moving in step (f_j)	country	R^2_j
Japan	2276	33,190	United States	57.9	United States	0.021
Denmark	264	27,174	Canada	58.3	Ireland	0.058
Norway	138	25,336	France	59.2	Canada	0.062
Germany	1232	24,343	Germany	61.1	U.K.	0.062
United States	7241	24,343	Portugal	61.2	Australia	0.064
Austria	139	23,861	Australia	61.4	New Zealand	0.064
Sweden	264	23,861	U.K.	63.1	Portugal	0.068
France	982	23,156	Denmark	63.1	France	0.075
Belgium	283	21,590	New Zealand	64.6	Denmark	0.075
Holland	100	20,952	Brazil	64.7	Austria	0.093
Singapore	381	20,131	Holland	64.7	Holland	0.103
Hong Kong	502	19,930	Belgium	65.0	Germany	0.114
Canada	815	19,149	Ireland	65.7	Norway	0.119
Finland	104	18,770	Pakistan	66.1	Indonesia	0.140
Italy	312	18,770	Sweden	66.1	Sweden	0.142
Australia	654	17,327	Austria	66.2	Finland	0.142
U.K.	1628	17,154	Italy	66.6	Belgium	0.146
Ireland	70	14,186	Norway	66.6	Hong Kong	0.150
New Zealand	137	12,965	Japan	66.6	Brazil	0.161
Spain	144	12,965	Chile	66.9	Philippines	0.164
Taiwan	353	10,698	Spain	67.0	Korea	0.172
Portugal	90	9,045	Indonesia	67.1	Pakistan	0.175
Korea	461	7,555	South Africa	67.2	Italy	0.183
Greece	248	7,332	Thailand	67.4	Czech	0.185
Mexico	187	3,944	Hong Kong	67.8	India	0.189
Chile	190	3,361	Philippines	68.8	Singapore	0.191
Malaysia	362	3,328	Finland	68.9	Greece	0.192
Brazil	398	3,134	Czech	69.1	Spain	0.192
Czech	87	3,072	India	69.5	South Africa	0.197
South Africa	93	2,864	Singapore	69.7	Columbia	0.209
Turkey	188	2,618	Greece	69.7	Chile	0.209
Poland	45	2,322	Korea	70.3	Japan	0.234
Thailand	368	2,186	Peru	70.5	Thailand	0.271
Peru	81	1,920	Mexico	71.2	Peru	0.288
Columbia	48	1,510	Columbia	72.3	Mexico	0.290
Philippines	171	880	Turkey	74.4	Turkey	0.393
Indonesia	218	735	Malaysia	75.4	Taiwan	0.412
China	323	455	Taiwan	76.3	Malaysia	0.429
Pakistan	120	424	China	80.0	China	0.453
India	467	302	Poland	82.9	Poland	0.569

Table 3. Description of main variables

Univariate statistics and simple correlation coefficients between main variables. Sample is 37 countries, except for the accounting standards index, which is available for 34 countries and the earnings co-movement index, which is available for only 25 counties. Numbers in parenthesis are probability levels at which the null hypothesis of zero correlation can be rejected in two-tailed tests.

Panel A. Univariate statistics and simple correlation coefficients between stock price synchronicity indices, stock return variance decomposition variables log($ó^2_{å}$) and log($ó^2_m$), and structural and institutional variables.

					Simple Correlation With			
variables	mean	stand-ard deviat-ion	min-imum	max-imum	$Ø_j$	$\tilde{O}_j$	*log($ó^2_{å}$)*	*log($ó^2_m$)*
Stock Co-movement Indices								
Average Fraction of Stocks Moving the Same Direction (f_j)	0.659	0.052	0.570	0.772	0.993 (0.00)	0.900 (0.00)	0.162 (0.34)	0.855 (0.01)
R square of market model based on weekly data for	0.169	0.099	0.020	0.429	0.888 (0.00)	0.949 (0.00)	0.146 (0.39)	0.891 (0.00)
Logistic Transformation of f_j for country *j* ($Ø_j$)	-0.808	0.501	-1.84	0.180	-			
Logistic transformation of R^2 for country *j* ($\tilde{O}_j$)	-1.76	0.758	-3.84	-0.284	0.909 (0.00)	-		
Logarithm of firm-specific variation (log($ó^2_{å}$))	-2.30	0.360	-3.05	-1.52	0.115 (0.50)	0.073 (0.67)	-	
Logarithm of market-wide variation (log($ó^2_m$))	-3.97	0.930	-5.60	-1.86	0.843 (0.00)	0.904 (0.00)	0.449 (0.00)	-
Logarithm of Per Capita GDP	8.94	1.30	5.71	10.4	-0.512 (0.00)	-0.457 (0.00)	-0.406 (0.01)	-0.573 (0.00)
Logarithm of Number Listed Stocks	5.61	1.06	3.81	8.89	-0.381 (0.02)	-0.307 (0.06)	0.200 (0.23)	-0.183 (0.28)
Structural Variables								
Logarithm of Geographical Size	12.7	2.11	6.46	16.1	-0.160 (0.34)	-0.0105 (0.54)	0.372 (0.02)	0.084 (0.62)
Variance in GDP growth	0.0001	0.0002	0.0007	0.001	0.0703 (0.68)	0.0999 (0.56)	-0.190 (0.26)	0.010 (0.97)
Industry Herfindahl Index	0.113	0.0559	0.030	0.281	0.0116 (0.94)	-0.035 (0.84)	-0.0175 (0.28)	-0.020 (0.00)
Firm Herfindahl Index	0.0482	0.0505	0.0001	0.219	-0.001 (0.99)	-0.126 (0.46)	-0.142 (0.38)	-0.148 (0.36)
Earnings Co-movement Index	0.383	0.164	0.055	0.777	0.0555 (0.80)	0.201 (0.35)	0.100 (0.63)	0.250 (0.23)
Institutional Variables								
Good Government Index	23.9	4.98	12.9	29.6	-0.552 (0.00)	-0.527 (0.00)	-0.477 (0.00)	-0.664 (0.00)
Accounting Standards Index	63.7	10.9	36	83	-0.237 (0.18)	-0.230 (0.19)	-0.034 (0.85)	-0.218 (0.22)
Anti-director Rights Index	1.78	1.93	0	5	-0.586 (0.00)	-0.595 (0.00)	0.271 (0.10)	-0.077 (0.65)

Panel B. Simple correlation coefficients of structural and institutional variables with each other.

	a	b	c	d	e	f	g	h	i
a. Logarithm of Per Capita GDP	-								
b. Logarithm of Number of Stocks Listed	0.364 (0.03)	-							
Structural variables									
c. Logarithm of Geographical Size	-0.371 (0.02)	0.111 (0.51)	-						
d. Variance in GDP growth	-0.020 (0.91)	-0.196 (0.24)	0.010 (0.97)	-					
e. Industry Herfindahl index	0.025 (0.88)	-0.674 (0.00)	-0.214 (0.20)	0.115 (0.50)	-				
f. Firm Herfindahl index	-0.020 (0.91)	-0.573 (0.00)	-0.040 (0.82)	0.091 (0.59)	0.710 (0.00)	-			
g. Earnings Co-movement index	-0.03 (0.88)	0.105 (0.63)	0.109 (0.61)	-0.100 (0.64)	-0.168 (0.43)	-0.325 (0.12)	-		
Institutional variables									
h. Good Government Index	0.919 (0.00)	0.335 (0.04)	-0.298 (0.07)	-0.010 (0.96)	-0.040 (0.82)	0.011 (0.95)	-0.126 (0.56)	-	
i. Anti-director Rights Index	0.706 (0.00)	0.403 (0.01)	-0.259 (0.12)	-0.292 (0.08)	-0.060 (0.73)	-0.070 (0.65)	-0.108 (0.61)	0.729 (0.00)	-
j. Accounting Standards Index	0.442 (0.01)	0.427 (0.01)	-0.090 (0.60)	-0.265 (0.13)	-0.552 (0.00)	-0.267 (0.13)	0.035 (0.87)	0.554 (0.00)	0.531 (0.00)

Table 4. Regressions of stock price synchronicity on economy structural variables.
Estimated coefficients from ordinary least squares regressions of stock price synchronicity variables, Ψ_j and Φ_j, on the logarithm of per capita GDP and structural variables. A control for market size, log(number of stocks), is included in all regressions. The structural variables are log(geographical size), variance of GDP growth, industry Herfindahl index, and the firm Herfindahl index. Regressions 4.2 and 4.4 include, as an additional structural variable, the earnings co-movement index. Sample is 37 countries, except for regressions on the earnings co-movement index, which is available for only 25 counties. Numbers in parenthesis are probability levels at which the null hypothesis of zero correlation can be rejected in two-tailed t-tests.

Dependent Variable	*Φ_j is a logistic transformation of the average fraction of stocks moving together*		*Ψ_j is a logistic transformation of the R_j^2 s of regressions of stock returns on market indices*	
	4.1	*4.2*	*4.3*	*4.4*
Intercept	4.36 (0.00)	8.11 (0.00)	4.66 (0.04)	8.04 (0.04)
Logarithm of Per Capita GDP	-0.189 (0.01)	-0.288 (0.01)	-0.238 (0.04)	-0.324 (0.04)
Logarithm of Number of Stocks Listed	-0.180 (0.11)	-0.200 (0.14)	-0.270 (0.13)	-0.367 (0.09)
Logarithm of Geographical Size	-0.867 (0.04)	-1.89 (0.02)	-0.948 (0.16)	-1.78 (0.15)
Variance in GDP growth	68.6 (0.84)	-253 (0.48)	228 (0.67)	-106 (0.85)
Industry Herfindahl index	-2.37 (0.27)	-4.30 (0.09)	-2.08 (0.54)	-5.70 (0.15)
Firm Herfindahl index	-0.446 (0.83)	1.49 (0.55)	-3.71 (0.26)	1.04 (0.80)
Earning co-movement index	-	0.375 (0.49)	-	1.09 (0.22)
F statistic for the regressions	3.88 (0.01)	3.51 (0.02)	2.87 (0.03)	2.50 (0.06)
sample size	37	25	37	25
R^2	0.44	0.59	0.36	0.51

Table 5: Regressions of stock price synchronicity on economy structural variables and a good government index.

Estimated coefficients from ordinary least squares regressions of stock price synchronicity variables, $\tilde{O}_i$ and $Ø_j$, on the logarithm of per capita GDP, structural variables and a good government index. A control for market size, log(number of stocks), is included in all regressions. The structural variables are log(geographical size), variance of GDP growth, industry Herfindahl index, and the firm Herfindahl index. Regressions 5.2 and 5.4 include, as an additional structural variable, the earnings co-movement index. Sample is 37 countries, except for regressions on the earnings co-movement index, which is available for only 25 counties. Numbers in parenthesis are probability levels at which the null hypothesis of zero correlation can be rejected in two-tailed t-tests.

Dependent Variable	$Ø_j$ is a logistic transformation of the average fraction of stocks moving together		$\tilde{O}_j$ is a logistic transformation of the R_j^2 s of regressions of stock returns on market indices	
	5.1	5.2	5.3	5.4
log(GDP per capita)	0.033	0.025	0.170	0.188
	(0.83)	(0.87)	(0.48)	(0.46)
Logarithm of Number of Stocks Listed	-0.204	-0.197	-0.315	-0.331
	(0.06)	(0.10)	(0.07)	(0.07)
Good Government Index	-0.059	-0.098	-0.110	-0.161
	(0.11)	(0.03)	(0.07)	(0.03)
Structural Variables				
Log. of Geographical Size	–0.811	–1.98	-0.846	-1.92
	(0.05)	(0.01)	(0.19)	(0.09)
Variance in GDP growth	72.1	-216	235	-47.2
	(0.82)	(0.49)	(0.65)	(0.93)
Industry Herfindahl index	-3.44[a]	–4.97	-4.07	-6.79
	(0.12)	(0.03)	(0.24)	(0.06)
Firm Herfindahl index	0.282	1.83	-2.38	1.59
	(0.89)	(0.41)	(0.46)	(0.65)
Earning comovement index	-	0.117	-	0.671
		(0.81)		(0.40)
F-test for the structural variables	1.91	2.93	1.67	1.78
	(0.14)	(0.05)	(0.19)	(0.17)
F statistics for the regression	3.89	4.63	3.19	3.55
	(0.00)	(0.00)	(0.02)	(0.01)
Sample size	37	25	37	25
R^2	0.48	0.70	0.44	0.64

Table 6. The Components of Stock Return Variation

Countries are ranked by stock market synchronicity, measured as the average R^2 of firm-level regressions of bi-weekly stock returns on local and U.S. market indexes in each country in 1995. This is decomposed into a firm-specific stock return variation, $\acute{o}^2_{\mathring{a}}$, and a market-wide stock return variation, $\acute{o}^2_m$. Returns include dividends and are trimmed at ±25%. Due to rounding errors, R^2_j does not exactly match $\acute{o}^2_m/(\acute{o}^2_m + \acute{o}^2_{\mathring{a}})$.

country	R^2_j	$\acute{o}^2_{\mathring{a}}$	$\acute{o}^2_m$	country	R^2_j	$\acute{o}^2_{\mathring{a}}$	$\acute{o}^2_m$
United States	0.021	0.174	0.004	Korea	0.172	0.174	0.036
Ireland	0.058	0.073	0.005	Pakistan	0.175	0.140	0.030
Canada	0.062	0.190	0.013	Italy	0.183	0.073	0.016
U.K.	0.062	0.068	0.005	Czech	0.185	0.125	0.028
Australia	0.064	0.149	0.010	India	0.189	0.132	0.031
New Zealand	0.064	0.111	0.008	Singapore	0.191	0.102	0.024
Portugal	0.068	0.084	0.006	Greece	0.192	0.103	0.024
France	0.075	0.087	0.007	Spain	0.192	0.067	0.016
Denmark	0.075	0.059	0.005	South Africa	0.197	0.074	0.018
Austria	0.093	0.061	0.006	Columbia	0.209	0.095	0.025
Holland	0.103	0.051	0.006	Chile	0.209	0.086	0.023
Germany	0.114	0.067	0.009	Japan	0.234	0.111	0.034
Norway	0.119	0.086	0.012	Thailand	0.271	0.109	0.041
Indonesia	0.140	0.127	0.021	Peru	0.288	0.128	0.052
Sweden	0.142	0.084	0.014	Mexico	0.290	0.129	0.052
Finland	0.142	0.113	0.019	Turkey	0.393	0.218	0.141
Belgium	0.146	0.047	0.008	Taiwan	0.412	0.084	0.058
Hong Kong	0.150	0.118	0.021	Malaysia	0.429	0.079	0.059
Brazil	0.161	0.143	0.027	China	0.453	0.079	0.066
Philippines	0.164	0.145	0.029	Poland	0.569	0.118	0.156

Table 7. Regressions of systematic or firm-specific stock price variation on economy structural variables and a good government index.

Ordinary least squares regressions of the logarithm of systematic stock return variation, log($ó^{2}_{m}$), and the logarithm of firm-specific stock return variation, log($ó^{2}_{å}$), on the logarithm of per capita GDP, structural variables and a good government index. A control for market size, log(number of stocks), is included in all regressions. The structural variables are log(geographical size), variance of GDP growth, industry Herfindahl index, and the firm Herfindahl index. Regressions 7.2 and 7.4 include, as an additional structural variable, the earnings co-movement index. Sample is 37 countries, except for regressions on the earnings co-movement index, which is available for only 25 counties. Numbers in parenthesis are probability levels at which the null hypothesis of zero correlation can be rejected in two-tailed t-tests.

Dependent Variable	log($ó^{2}_{m}$) is the logarithm of average systematic returns variation		log($ó^{2}_{å}$) is the logarithm of average firm-specific returns variation	
	7.1	7.2	7.3	7.4
log(GDP per capita)	0.228	0.248	0.057	0.059
	(0.38)	(0.42)	(0.63)	(0.67)
Logarithm of Number of Stocks Listed	-0.176	-0.313	0.140	0.0500
	(0.34)	(0.17)	(0.10)	(0.63)
Good Government Index	-0.164	-0.213	-0.0540	-0.0520
	(0.01)	(0.02)	(0.06)	(0.17)
Structural Variables				
Log. of Geographical Size	-0.418	-0.128	0.430	1.79
	(0.54)	(0.92)	(0.17)	(0.01)
Variance in GDP growth	9.59	-211	228	-167
	(0.99)	(0.73)	(0.37)	(0.55)
Industry Herfindahl index	-3.81	-6.59	0.256	0.213
	(0.30)	(0.12)	(0.88)	(0.91)
Firm Herfindahl index	-1.89	1.26	0.481	-0.317
	(0.58)	(0.77)	(0.76)	(0.87)
Earning comovement index	-	0.621	-	-0.051
		(0.51)		(0.91)
F statistics for the regression	4.29	3.26	3.18	3.42
	(0.00)	(0.02)	(0.01)	(0.02)
Sample size	37	25	37	25
R^2	0.51	0.62	0.43	0.63

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Table 8. Regressions of systematic or firm-specific stock price variation on economy structural and institutional development variables across countries with good government.
Ordinary least squares regressions of the logarithm of systematic stock return variation, log($ó_{m}^{2}$), and the logarithm of firm-specific stock return variation, log($ó_{å}^{2}$), on the logarithm of per capita GDP, structural variables and either a good government index, an index of investor rights against corporate insiders, or both. A control for market size, log(number of stocks), is included in all regressions. The structural variables are log(geographical size), variance of GDP growth, industry Herfindahl index, and the firm Herfindahl index. Regressions 8.4 and 8.8 include, as an additional structural variable, the earnings co-movement index. The sample consists of the 22 countries whose good government index is above the average for the full sample of 37 countries. Numbers in parenthesis are probability levels at which the null hypothesis of zero correlation can be rejected in two-tailed t-tests.

Dependent Variable	log($ó_{å}^{2}$) is the logarithm of average firm-specific returns variation				log($ó_{m}^{2}$) is the logarithm of average systematic returns variation			
	8.1	*8.2*	*8.3*	*8.4*	*8.5*	*8.6*	*8.7*	*8.8*
log(per capita GDP)	-0.279 (0.45)	0.058 (0.82)	0.119 (0.73)	0.172 (0.63)	0.350 (0.64)	-0.156 (0.83)	0.546 (0.53)	0.450 (0.63)
log of number of stocks listed	0.140 (0.25)	0.040 (0.67)	0.027 (0.80)	0.026 (0.81)	-0.294 (0.24)	-0.188 (0.46)	-0.350 (0.22)	-0.349 (0.23)
Good government index	0.036 (0.68)	-	-0.022 (0.77)	-0.024 (0.76)	-0.226 (0.21)	-	-0.254 (0.19)	-0.251 (0.22)
Anti-director Rights Index	-	0.168 (0.01)	0.173 (0.02)	0.173 (0.02)	-	0.022 (0.89)	0.085 (0.60)	0.085 (0.62)
Structural Variables								
Logarithm of Geographical Size	0.289 (0.47)	0.383 (0.21)	0.421 (0.22)	0.431 (0.22)	-0.439 (0.59)	-0.818 (0.32)	-0.374 (0.66)	-0.391 (0.66)
Variance in GDP growth	-500 (0.13)	-20.3 (0.95)	-3.29 (0.99)	-16.4 (0.96)	-446 (0.50)	-399 (0.63)	-201 (0.81)	-177 (0.84)
Industry Herfindahl index	1.37 (0.62)	0.918 (0.62)	0.541 (0.81)	0.803 (0.74)	-4.93 (0.39)	-.969 (0.85)	-5.34 (0.37)	-5.80 (0.36)
Firm Herfindahl index	-1.70 (0.50)	-1.67 (0.33)	-1.34 (0.53)	-1.60 (0.47)	-2.22 (0.67)	-5.97 (0.21)	-2.04 (0.70)	-1.56 (0.78)
Earning co-movement index	-	-	-	-0.319 (0.56)	-	-	-	0.569 (0.68)
Joint Significance F test for the regression	1.41 (0.28)	3.37 (0.03)	2.77 (0.05)	2.38 (0.08)	1.00 (0.47)	0.680 (0.68)	0.870 (0.57)	0.740 (0.67)
sample size	22	22	22	22	22	22	22	22
R^2	0.41	0.63	0.63	0.64	0.33	0.25	0.35	0.36

Figure 1. Observed stock price synchronicity in the stock markets of selected countries. The fraction of stocks whose prices rise each week of 1995 in the stock markets of China, Malaysia, Poland and the United States based on returns including dividend income from Datastream.

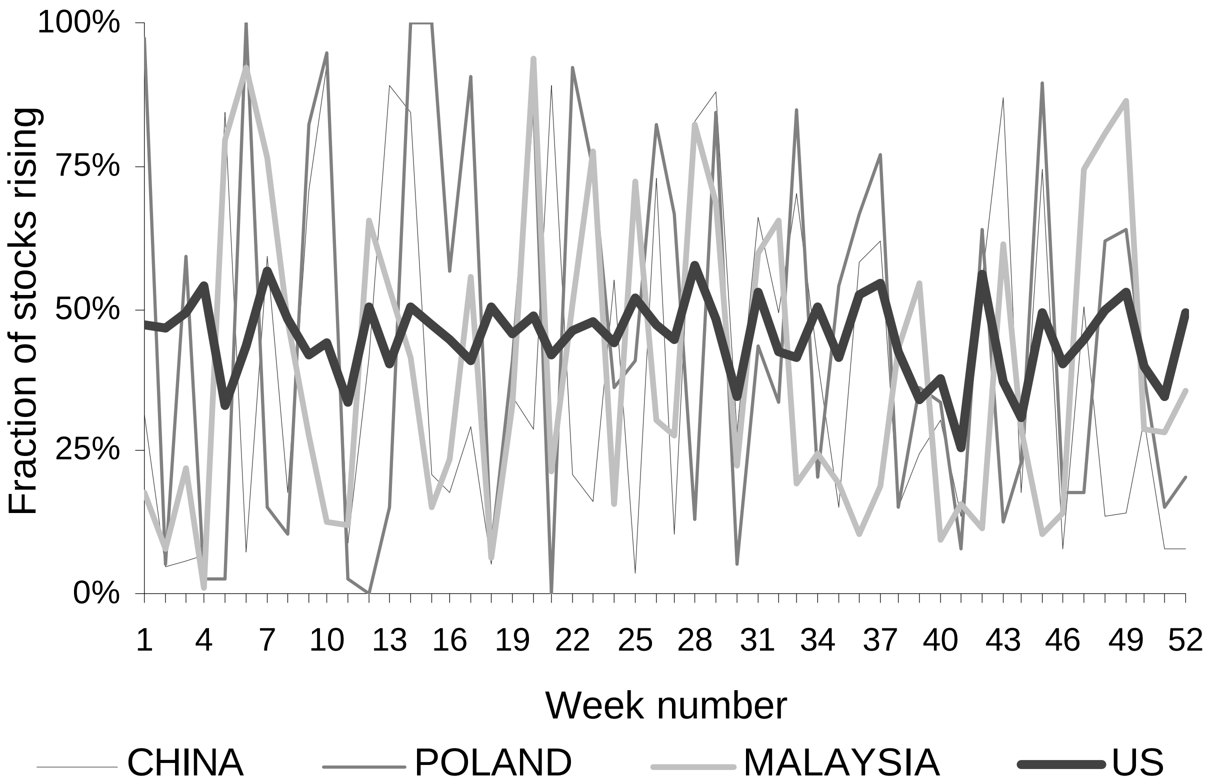


Figure 2. The declining synchronicity of U.S. stock prices
The fraction of stocks moving together each month from 1926 to 1995 using all available U.S. stocks and using a portfolio of 400 stocks randomly chosen each month. Returns include dividend income and are from the Center for Research in Securities Prices.

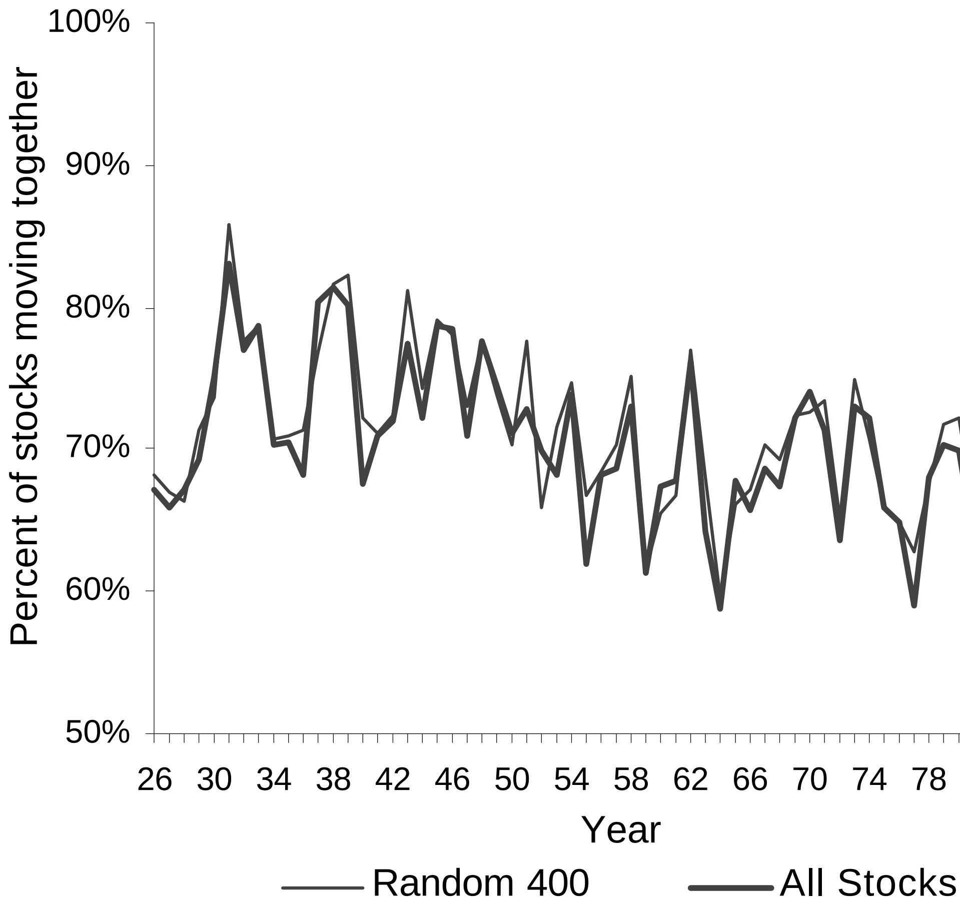


Figure 3. The declining fraction of U.S. stock return variation explained by the market. The fraction of U.S. stock return variation explained by the value-weighted market index is estimated by running a simple market model regression of using monthly returns including dividend income for sequential disjoint four year periods from 1926 to 1995, using all available U.S. stocks and a portfolio of 400 stocks randomly chosen each period. Returns and indexes include dividend income and are from the Center for Research in Securities Prices.

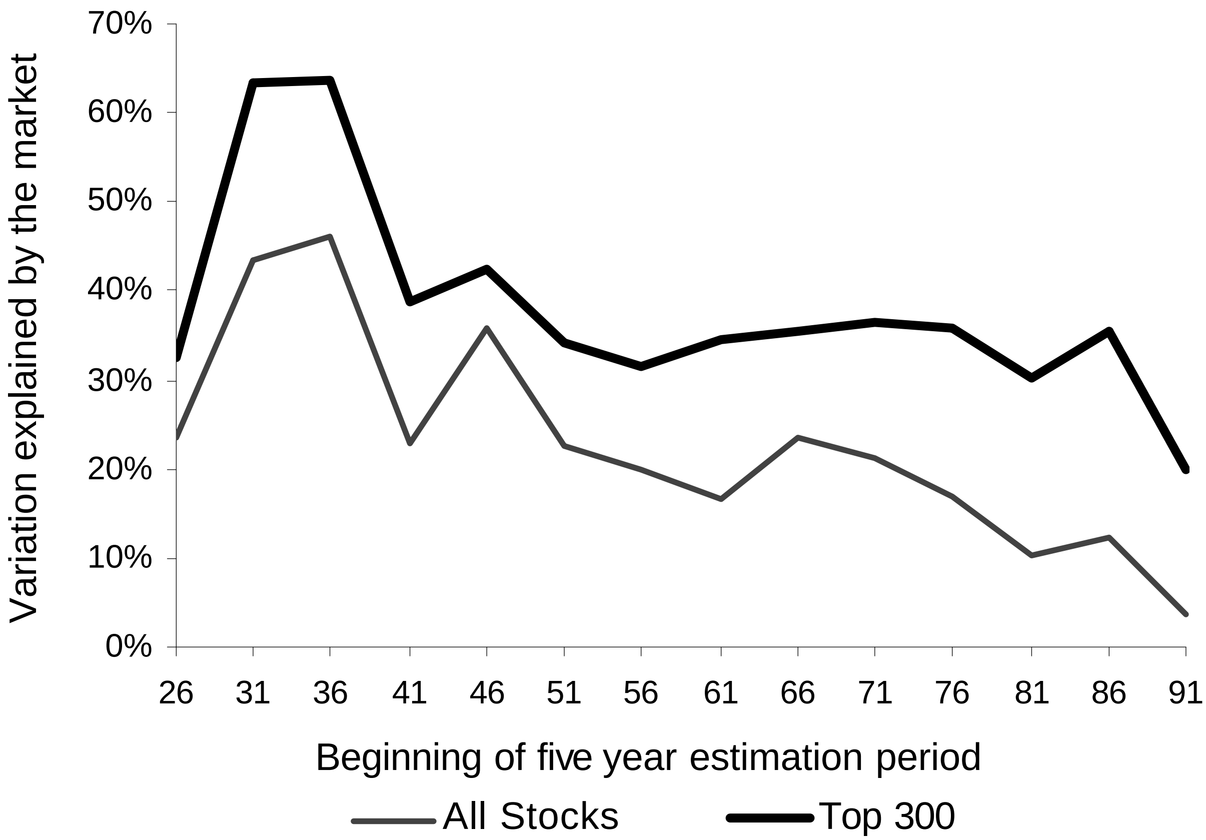
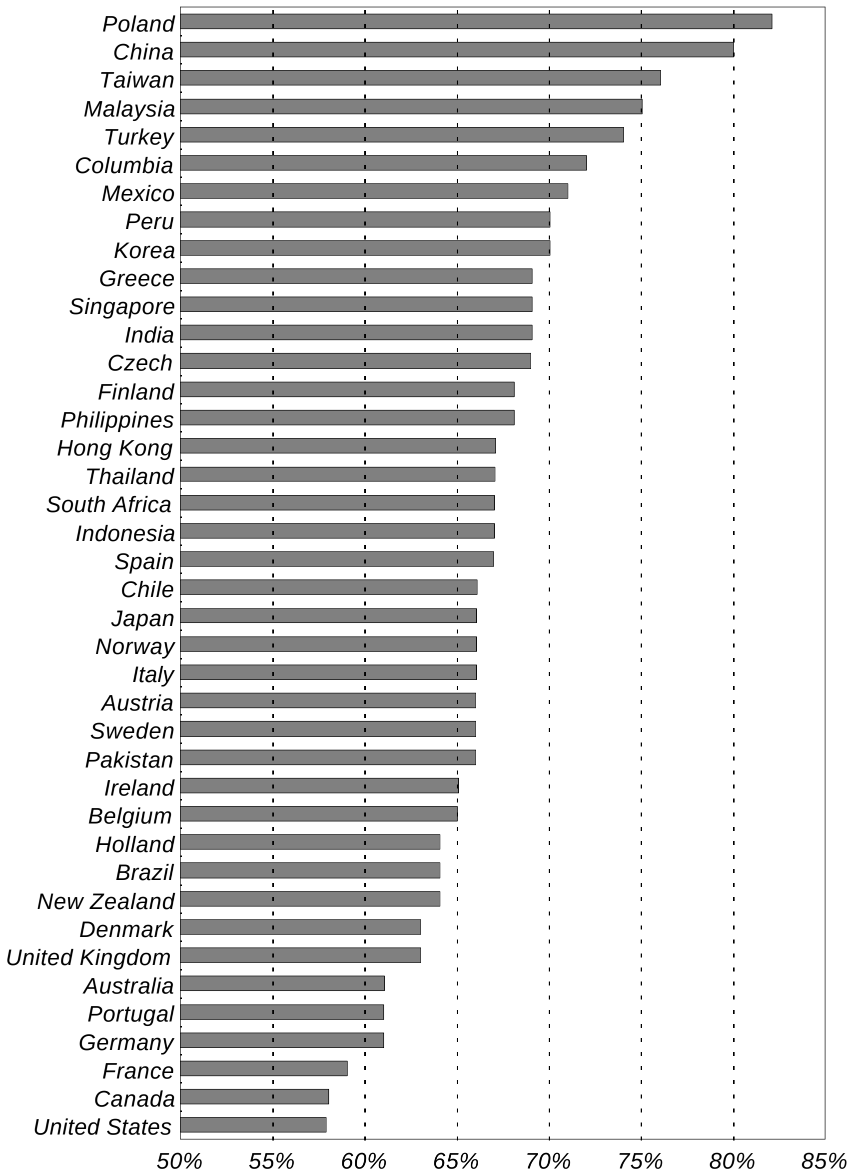


Figure 4. Stock price synchronicity in various countries

Panel A. Stock price synchronicity measured by the average fraction of stock prices moving in the same direction during an average week in 1995. Stock prices that do not move during a week are excluded from the average for that week. Price movements are adjusted for dividend payments, and are based on Datastream total returns.



Percent of stocks moving in the same direction by country

Panel B. Stock price synchronicity measured by the average percent of total biweekly firm-level return variation in 1995 explained by local and U.S. value-weighted market indexes. Stock returns and indexes include dividend payments, and are obtained from Datastream.

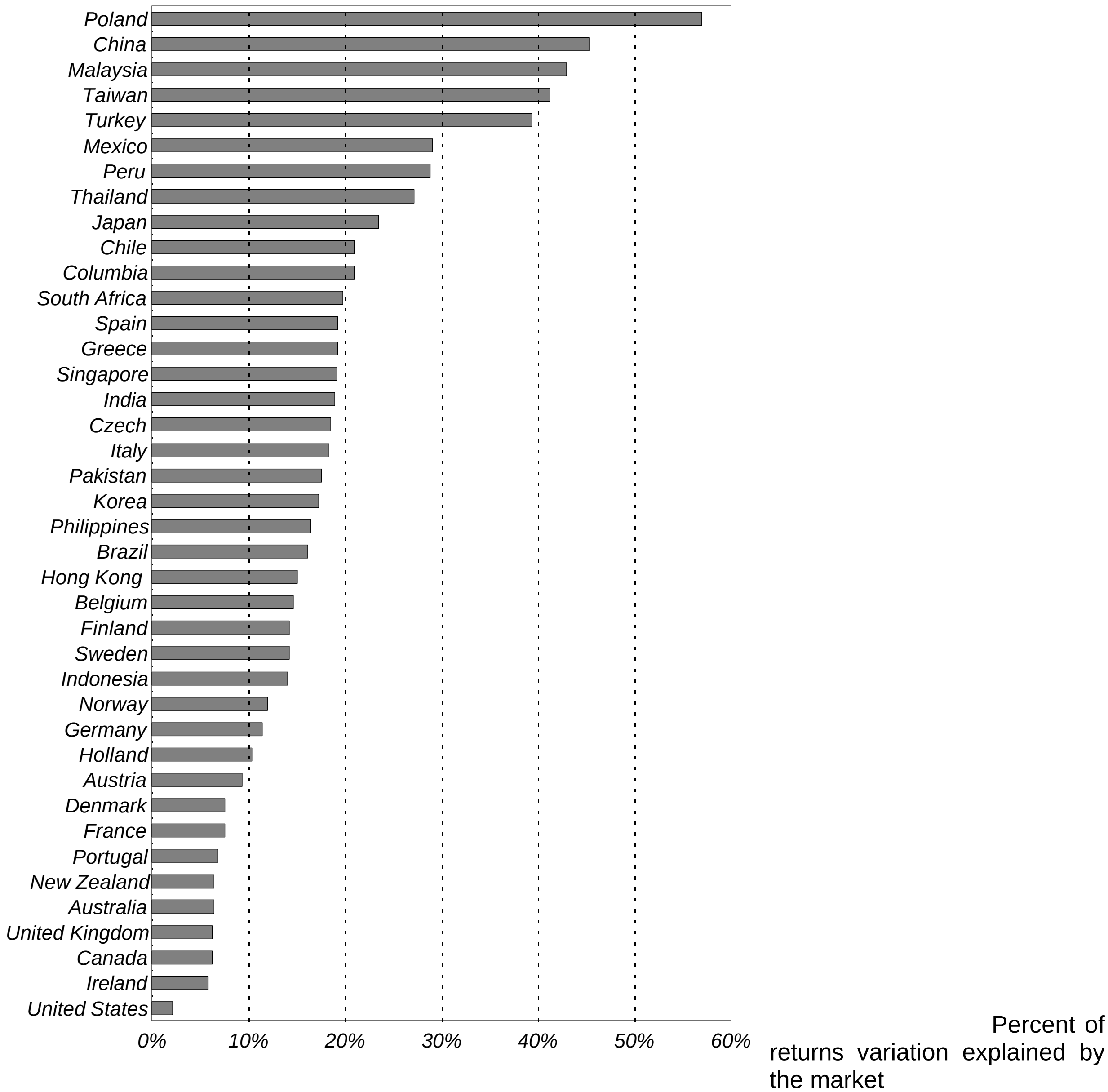
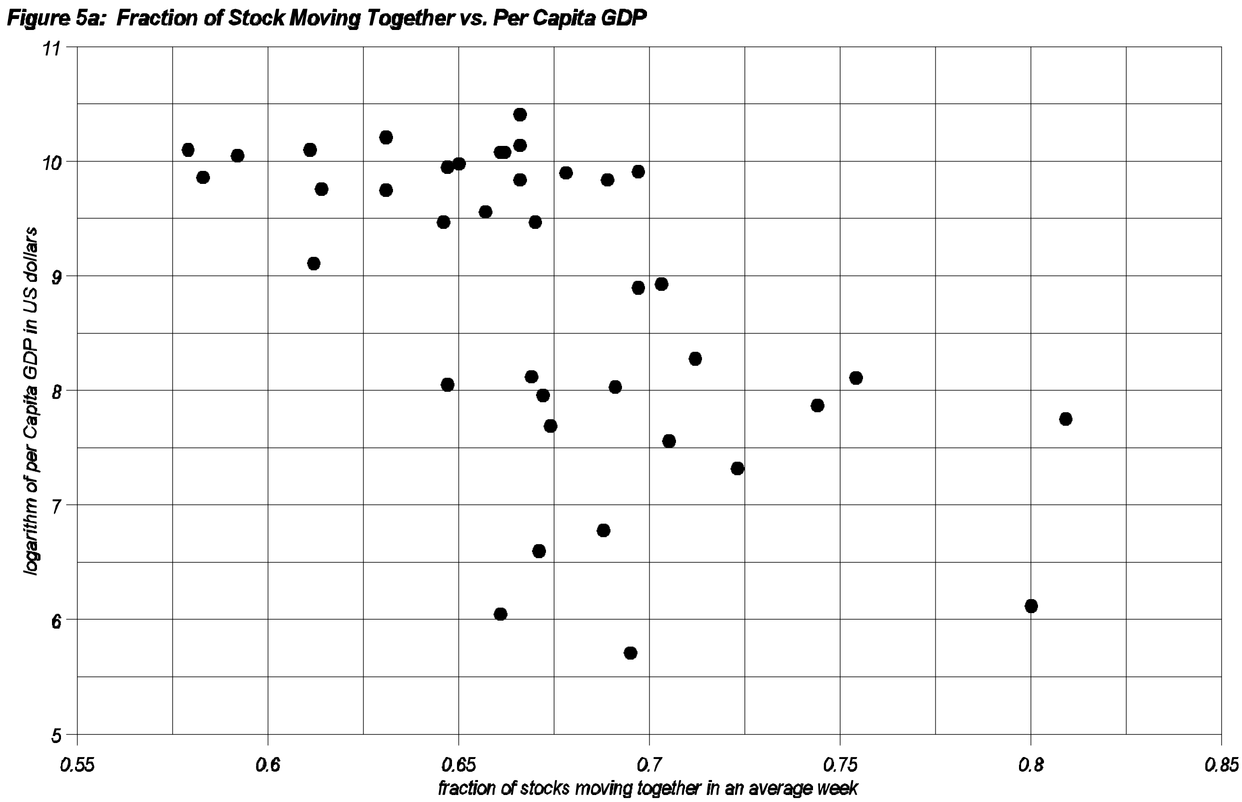


Figure 5. Stock price synchronicity and gross domestic product

Panel A. The logarithm of per capita gross domestic product plotted against stock return synchronicity measured by the average percent of stock returns moving in the same direction each week. Each observation is for one country. Data are for 1995.



Panel B. The logarithm of per capita gross domestic product plotted against stock return synchronicity measured by the percent of total return variation explained by local and U.S. value-weighted market indexes in ordinary least squares regressions. Each observation is for one country. Returns and indexes include dividends. Data are for 1995.

Figure 5b: The Importance of Market Returns vs. Per Capita GDP

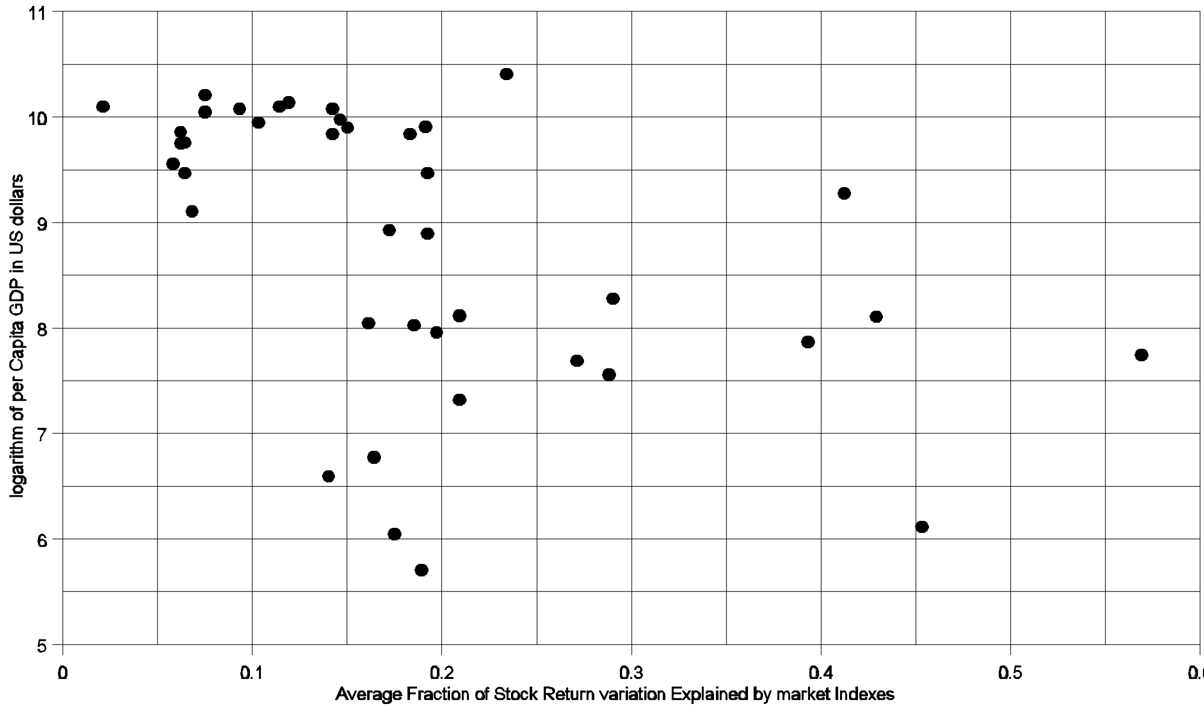


Figure 6. The changing structure of U.S. stock return variation from 1926 to 1995
Total returns variation is decomposed into a systematic component, which is related to the value-weighted market index, and a firm-specific component, which is not. Each bar represents an estimate over a three year period based on monthly dividend-adjusted returns. Returns and indexes include dividends. Data are from the Center for Research in Securities Prices.

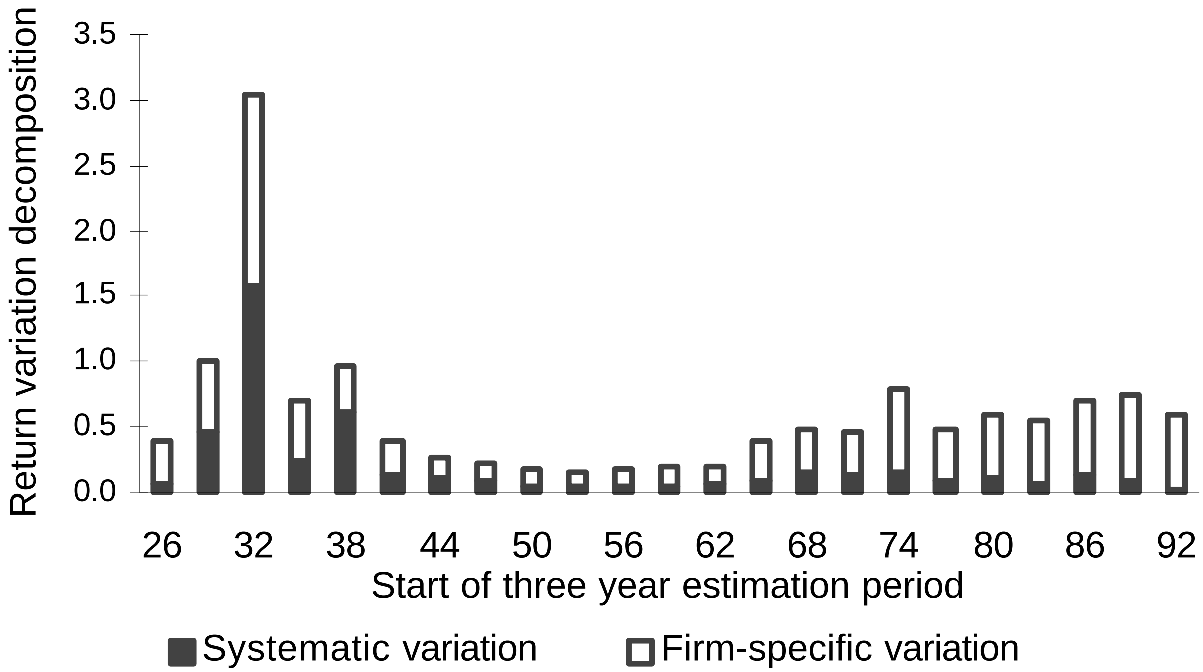
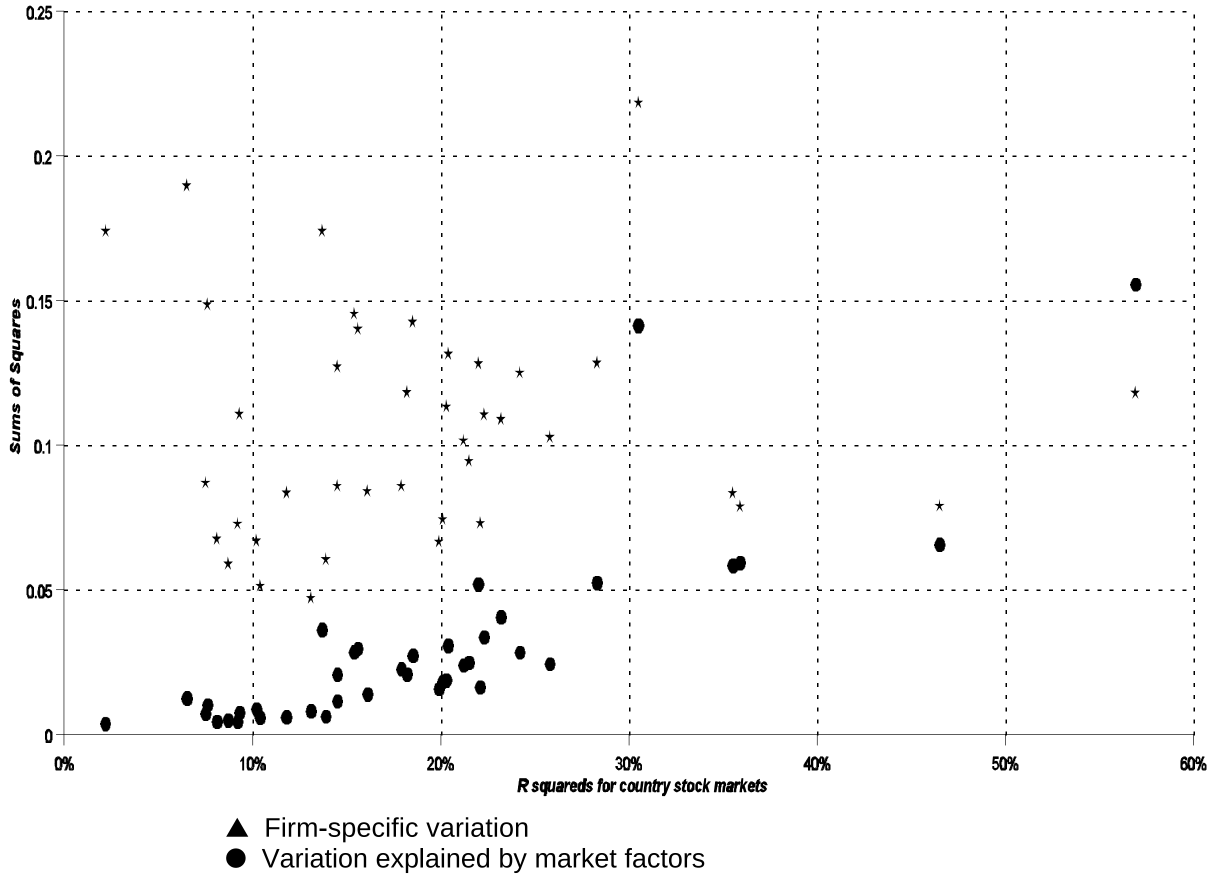


Figure 7. Average stock return variation decomposed into a systematic component, $ó_m^2$, and a firm-specific stock component, $ó_å^2$, plotted against stock return synchronicity, as measured by systematic variation as a percent of total variation. Biweekly 1995 firm-level returns are regressed on local and U.S. value-weighted indexes to construct this data. Returns and indexes are adjusted for dividends, and are from Datastream.



Notes

1. At present, we only have a long panel of returns for the US. We are beginning our exploration of other historical patterns of advanced economies.

2. Although the R_j^2 for the U.S. stock markets is lower than that reported by Roll (1988), note that we use 1995 biweekly data while he uses monthly data from September 1982 to August 1987. Our R^2 estimate for the US market in the early 1980s ranges between 12 and 13% (see Figure 3), and so is much closer to the average R^2 of 0.179 he reports.

3. We are grateful to Alan Deardorf and seminar participants at the University of Arizona, the University of British Columbia, George Mason University, Texas A&M University, and Tulane University for stressing the need to include a "country size" effect.

4. We are grateful to Michael Weisbach and an anonymous referee for stressing this clustering effect, and suggesting we consider it more thoroughly.