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Contents

Scott Mixon, Option markets and implied volatility: Past versus present 171
David Berger, Alain Chaboud and Erik Hjalmarsson, What drives volatility persistence in the foreign exchange market? 192
Kuntara Pukthuanthong and Richard Roll, Global market integration: An alternative measure and its application 214
Evan W. Anderson, Eric Ghysels and Jennifer L. Juergens, The impact of risk and uncertainty on expected returns 233
Po-Hsuan Hsu, Technological innovations and aggregate risk premiums 264
Rachel M. Hayes and Scott Schaefer, CEO pay and the Lake Wobegon Effect 280
Renée B. Adams and Daniel Ferreira, Women in the boardroom and their impact on governance and performance 291
Amit Goyal and Alessio Saretto, Cross-section of option returns and volatility 310
Adam C. Kolasinski, Subsidiary debt, capital structure and internal capital markets 327

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Global market integration: An alternative measure and its application ☆

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A R T I C L E I N F O

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Global markets seem to be increasingly integrated but there is no well-accepted measure of integration. We show that the correlation across markets is a poor measure; perfectly integrated markets can exhibit weak correlation. We derive a new integration measure based on the explanatory power of a multi-factor model and use it empirically to investigate recent trends in global integration. For most countries, there has been a marked increase in measured integration over the past three decades, but this is not indicated by correlations among country indexes.

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1. Introduction

Capital mobility and free trade, which are hallmarks of cross-country market integration, characterize the wealthiest nations and appear to benefit many citizens. Investors probably favor the flexibility of financial market integration even though some politicians seem occasionally to argue for isolation and protectionism. The degree of integration may seem intuitively apparent to many, but quantitative measures of integration have not often agreed with the intuition. We think there is a simple explanation: some quantitative integration measures are flawed (and the intuition is correct).

We explain a fundamental flaw in the most widely used measure of integration, cross-country correlations of stock index returns. Theoretically, such correlations can be small even when two countries are perfectly integrated. This occurs whenever there are multiple global sources of return volatility and countries do not share the same sensitivities to all of them. Indeed, the returns of two countries can be 100% explained by global factors yet be only weakly correlated.

A sensible intuitive quantitative measure of financial market integration is the proportion of a country's returns that can be explained by global factors. If that proportion is small, the country is dominated by local or regional influences (see Stulz, 1981; Errunza and Losq, 1985; Stulz,

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1987). But if a group of countries is highly susceptible to the *same* global influences, there is a high degree of integration.

Some have suggested that a single asset pricing model applies to all perfectly integrated countries (Solnik, 1974; Sercu, 1980; Stulz, 1981; Adler and Dumas, 1983). We have nothing to contribute to this asset pricing issue, but instead frame our empirical investigation within a broader concept of integration that depends entirely on the high frequency (daily) return generating process. We contend that markets could be globally integrated even if assets were irrationally priced so long as the *same* global shocks permeate all countries. We do not mean to say that all or any shocks *are* irrational, but if some are, markets would still be integrated if the same irrationalities propagate globally.

This paper first reviews some previous literature on measures of market integration, then explains why simple correlations are problematic, and then derives and applies global factors empirically. As measured by our new quantitative metric, market integration has grown substantially over the past 35 years in most of the 81 countries for which daily stock index data are available. There are, however, some exceptions, mostly countries that would have been intuitive candidates for poor integration.

2. Previous literature on measuring market integration

Dumas, Harvey, and Ruiz (2003) argue that stock market returns do not completely reflect economic fundamentals within each country. They go on to quantify the magnitudes of the changes in correlations that can be due to integration alone.

Carrieri, Errunza, and Hogan (2007) use generalized autoregressive conditional heteroskedasticity (GARCH)-in-mean methods to assess the evolution in market integration of eight emerging economies over the period 1977–2000. They provide evidence about the impropriety of assessing integration by the correlations of market wide index returns. They show that correlations of country index returns with the world are significantly lower than estimated integration indices based on real activity.

Hardouvelis, Malliaropoulos, and Priestley (2006) examine whether the introduction of a single currency reduced intra-European currency risk and, to the extent that currency risk is priced, reduced the overall exchange rate exposure of European stocks. They trace the changing integration of European markets during the 1990s by the relative influence of EU-wide risk factors over country-specific risk factors.

Schotman and Zalewska (2006) test market integration in Central Europe. They measure integration by the R-square between a developing market (e.g., Hungary, Czech Republic, or Poland) and a developed market (e.g., U.S. or Germany). They take account of autocorrelation, but their R-square is really quite similar to the traditional method of measuring integration by correlation. Curiously, they argue that integration should be measured by the "impact coefficient" or the "beta" in a regression of the developing country's return on the developed country's return. But this cannot be correct; integration could be complete and yet the beta could be quite low if the developing country is simply concentrated in lower risk industries.

Bekaert and Harvey (1995) examine market integration with a sample of 12 emerging markets plus the developed markets comprising the Morgan Stanley Capital International index. They were perhaps the first to explicitly model time variation in expected returns induced by changing covariance with a single global factor. More recent contributions include Aydemir (2004), Chambet and Gibson (2008), Bekaert, Harvey, Lundblad, and Siegel (2008), and Eiling and Gerard (2007).

Chambet and Gibson (2008) focus on emerging markets during the most recent decade; they develop a model consisting of global and local factors plus a systematic emerging markets factor. Their paper is insightful because it integrates their measure of financial integration with indicators of real activity, particularly trade openness and trade concentration. They find that many emerging markets remain non-integrated but the degree of segmentation depends on the country's trade diversification, less diversified countries being more financially integrated.

The recent paper by Bekaert, Harvey, Lundblad, and Siegel (2008) provides a unique approach. For each country, they first calculate the difference between each industry's earnings yields in the country and in the world. Their measure of a country's segmentation (the opposite of integration) is an industry weighted average of these absolute earnings yield differences. They relate this measure to a battery of different possible explanatory factors and they find, like Chambet and Gibson, that emerging markets are still segmented, though the degree of integration has improved.

Eiling and Gerard (2007) model market integration by the proportion of return variance explained by a single global factor relative to the total variance of a country's returns. They also check for regional as opposed to global influences and present some sophisticated tests of time variation. However, using a single global factor (the approach followed by Eiling and Gerard) might fail to reveal some relevant information about the true extent of market integration. An explanation for this potential difficulty is provided in the next section.

Brooks and Del Negro (2004a) develop a latent factor approach that is probably the closest to the methods used in this paper. Their focus, however, is on individual firms and how those firms' returns can be decomposed into global, country, industry, and idiosyncratic components. Our focus is strictly on broad well-diversified indexes of stocks in each country, so the idiosyncratic component is minimal; we then ask how much of the remaining return is global and how much is left to be explained by the country.

3. Correlation and integration; imperfect companions

Suppose we wish to measure the degree of integration between countries A and B. For ease of illustration, assume

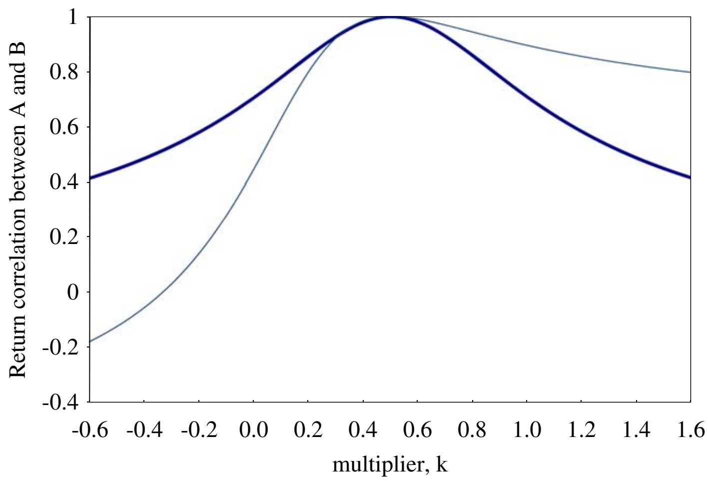

Fig. 1. Return correlation between perfectly integrated countries. There are two countries, A and B, whose market index returns are completely determined by two global factors conforming to Eq. (1) of the text but with zero residual (country-specific) volatility; i.e., $R(j,t)=a(j)+\beta(j,w)*f(w,t)+\beta(j,s)*f(s,t)$ is the return for country j in time t, $a(j)$ is a constant, $\beta(j,w)$ and $\beta(j,s)$ are factor sensitivities for country j to the two global factors, $f(w,t)$ and $f(s,t)$ respectively. Since the returns for both countries are completely determined by the global factors, the countries are perfectly integrated. For simplicity of illustration, the figure assumes that $\text{Var}[f(w,t)]=\text{Var}[f(s,t)]$, so the factor sensitivities (β's) determine the volatility contributions of factors to the country return. The multiplier, k, is simple indicator of cross-country differences in factor sensitivity; specifically $\beta(B,w)=k\beta(A,w)$ and $\beta(B,s)=(1-k)\beta(A,s)$. For $k=1-k=\frac{1}{2}$, both sensitivities are half as large in country B as in country A and, as the figure shows, the return correlation is perfect. For all values of $k\neq\frac{1}{2}$, the correlation is strictly less than +1. The effect of differing relative sensitivities between w and s are illustrated by $\beta(A,w)=\beta(A,s)$, the heavier curve, or $\beta(A,w)=2\beta(A,s)$, the lighter curve.

that there are exactly two truly global industry factors, say water and salt. Each country's stock market return is driven by a two-factor model with these same two factors;

$$R(j,t)=a(j)+\beta(j,w)f(w,t)+\beta(j,s)f(s,t)+e(j,t) \quad \text{for } j=A,B, \tag{1}$$

where $R(j,t)$ is the return of country j's broad market (well-diversified) index at time t, the β's are sensitivity coefficients and the f's are global factors at time t with "w" indicating water and "s" indicating salt.

We claim that these two countries are completely integrated when $e(A,t)=e(B,t)=0$ for all t. In such a case, their returns are completely driven by the same global factors and there are no residual country-specific return components independent across the countries. What does this imply for the correlation between their broad index returns? It is straightforward to prove that the correlation of $R(A,t)$ and $R(B,t)$ is less than +1 provided that the following condition is not met: $\beta(A,w)=k\beta(B,w)$ *and* $\beta(A,s)=k\beta(B,s)$ for some positive constant k. If both "betas" are exactly proportional across the two countries, the correlation is +1; otherwise it is not.[1]

These betas can be different in the two countries for several reasons. The simplest reason is that one country produces more water and the other country produces more salt, so the coefficients are larger for the industry that is more significant for that country. The betas could also differ because of leverage, industrial structure, and stock market representation, etc. The point is that perfect integration in the sense of being completely and exclusively driven by the SAME global factors does not imply perfect correlation.

If there are more than two factors driving returns in each country, as there almost certainly are,[2] even when just industry factors are considered, then an analogous condition obtains; unless all the betas in one country are proportional to the betas in its companion country, the simple correlation of country returns is strictly less than +1. The difference between the observed correlation and perfect correlation depends on the cross-sectional spread of factor volatilities and on how different the profiles of sensitivities (betas) are in the two countries. If the e's are not zero, then the correlations are even smaller. This suggests that a better measure of integration is $1-\text{Var}(e)/\text{Var}(R)$; i.e., the R-square from the multi-factor model.

Fig. 1 illustrates the impact of multiple factors for inter-country return correlations using just two factors, as in (1) above, but with non-proportional betas across the two countries. For convenience and without loss of generality, the two factors are assumed to have the same volatility[3] but the betas conform to the relations,

$$\beta(A,w)=k\beta(B,w) \quad \text{and} \quad \beta(A,s)=(1-k)\beta(B,s)$$

for differing values of the constant, k. Two different curves are illustrated, one for equal betas in country A, $\beta(A,w)=\beta(A,s)$, and another for different betas, $\beta(A,w)=2\beta(A,s)$. In both cases, when the betas of the two countries are proportional, $k=(1-k)=0.5$, the correlation is perfect while for all other values of k, it is less than 1.0. For $k=0.5$, though the correlation is +1, country B has half the volatility of country A with respect to both factors w and s.

[1] This is a straightforward application of the famous Cauchy inequality.

[2] In Section 4, we present empirical evidence for the existence of several global factors.

[3] Since the factors have the same volatility, the factor sensitivities (the β's) determine the contribution of each factor to the country's return volatility.

The figure allows k to vary from -0.6 to 1.6, but the betas have the same sign in the two countries only in the range $0<k<1$. However, it seems quite possible that some countries could actually have betas with opposite signs; this might occur, for example, if one country is a major oil exporter and another is a major oil importer. Then the oil factor would increase market returns in one country and decrease them in the other.

The figure makes clear, too, that the relative importance of the two factors has a material influence on the inter-country correlation. When the sensitivities are the same in country A, the correlation falls off symmetrically as k changes in either direction. Also, the correlation remains fairly large over a wide range of k; it exceeds 0.7 for $0<k<1$, the range in which betas have the same sign in both countries. However, for somewhat unequal betas in country A (the case illustrated is $\beta(A,w) = 2\beta(A,s)$), the impact of k is quite asymmetric. For $k>0.5$, the correlation remains above 0.8 all the way out to $k = 1.6$ while for $k<0.5$, the correlation drops rapidly and eventually becomes negative (for $k<-0.3$). This makes intuitive sense because w is a more important source of variation than s.

Note that whatever the value of k, the two countries A and B illustrated in Fig. 1 are perfectly integrated because the R-square is 1.0 in a multiple regression of each country's market index returns on both factors. Clearly, the simple correlation between the country returns leaves a lot to be desired as a measure of integration while the multiple R-square provides a perfect indicator.

Recently, Carrieri, Errunza, and Hogan (2007), (hereafter CEH), derive a seemingly similar measure of integration, essentially an R-square from a regression of an index of "ineligible" securities on *all* eligible securities, where ineligible assets are those that can be bought and sold only by investors in a particular market and eligible assets are those than can be traded by anyone in the world. The CEH formulation is based on the international asset pricing theory of Errunza and Losq (1985), which includes both a global risk premium and a "super" risk premium for ineligible assets.

CEH cogently emphasize that simple correlations are poor measures of integration; we agree completely. But our R-square integration measure is much simpler intuitively than the CEH measure. Moreover, it does not depend on any particular asset pricing model but merely requires globally common factors. Perhaps most important for empirical work, our measure does not require a categorization into ineligible and eligible assets, which could be a difficult task.

We readily admit, however, that any empirical implementation of CEH is likely to produce something rather similar to the implementation of our measure. The basic reason is the sheer infeasibility of using the entire world's "eligible" assets as regressors; they number in the tens of thousands. Indeed, CEH used a limited number of regressors including the Morgan Stanley Capital International industry factors. Hence, their empirical implementation is tantamount to regressing country returns on a set of global factors.

When there really are several global factors, attempting to measure market integration by relying on the assumption that there is just one global factor, as in Eiling and Gerard (2007), is subject to a problem similar to that encountered when using simple correlations. Indeed, if the model employed has only a single global factor and a country-specific source of volatility that is unrelated across countries, then the proportion of return variance explained by the global factor is closely related to simple correlations. To see this relation, imagine that the assumed return generating process is a variant of (1), viz.,

$$R(j,t) = a(j) + \beta(j,g)f(g,t) + e(j,t) \quad \text{for } j = A, B, \tag{2}$$

where g now denotes the single global factor. If the variance of the country-specific influence, $e(j,t)$ is zero for both countries A and B, the R-square in (2) will be 1.0. In this case, the correlation between the returns of A and B will also be +1. As the volatility of $e(j,t)$ grows relative to the volatility of $\beta(j,g)f(g,t)$, for both A and B, the correlation will fall; it will be zero for $\beta(A,g) = \beta(B,g) = 0$. In this sense, there will be a close correspondence between the simple inter-country correlation coefficient and the adjusted R-squares from model (2).

This correspondence will be diminished, however, if $e(A,t)$ is correlated with $e(B,t)$. For example, Eiling and Gerard (2007) include regional factors, influences that affect only a subset of countries but not all countries. They argue, correctly in our opinion, that the proportion of return variance explained by the global factor alone, not including anything explained by the regional factors, is a better measure of global market integration than simple correlations.[4] Still, that proportion cannot be as trustworthy a measure of integration as the proportion of variance jointly explained by *multiple* global factors, provided that they number two or more and that all countries do not have proportional betas.

Another important recent paper related to ours is Bekaert, Hodrick, and Zhang (2008), (hereafter BHZ). Their data are different, weekly returns for individual large firms in 23 developed countries from 1980–2005 as opposed to our daily data for broad market index returns in 81 developed and developing countries from the 1960s to 2007. However, a more pronounced difference is their method of analysis.

The essence of their evaluation of comovement is described as follows:

> Assuming the residual covariances [from a factor model] to be zero, …covariances between two assets estimated in different time periods can increase through the following two channels: an increase in the factor loadings…or an increase in the factor covariances. If an increase in covariance is due to increased exposure to the world market, the change in covariance is much more likely to be associated with the process of global market integration…, (BHZ, 2008, p. 7).

[4] Regional factors could explain regional integration that is not global in scope.

BHZ structure individual firms to obtain global, regional (for three regions), industry, and style portfolios. They thoroughly investigate the fit of several multi-factor models and provide persuasive evidence that risk-based models such as Fama-French (1998) or the arbitrage pricing theory (APT) do better than other widely cited models such as Heston-Rouwenhorst (1994). BHZ also provide insights into other controversial subjects such as the relative influence of industry versus country returns and the presence of contagion during crises. The BHZ paper contains a number of important empirical findings for international finance.

But BHZ (2008, p. 18) emphasize that, "The main goal of our empirical work is to assess whether correlations display trending behavior (as brought about by the process of globalization, for example)." Although they qualify a strict connection between country correlations and integration,[5] their empirical work is clearly intended to impute evidence about integration from the pattern of correlation; "…the gradual nature of the globalization process itself make(s) a trend test the most suitable test to examine a permanent change in correlations," (p. 21).

They find "…little evidence of a trend in country return correlations, except in Europe. Even there, we cannot ascribe the risk in comovements with much confidence to an increase in betas with respect to the factors, which would make it more likely that the increase is permanent" (p. 27).

Their main empirical result stands in stark contrast to our own, which makes it incumbent on us to provide an explanation. The most important distinction between the two approaches is encapsulated in the quoted paragraph from their page 7 above. The beginning phrase, "Assuming the residual covariances to be zero…" says it all. Our concept of integration is effectively based on the size of the country-specific residual variance in a factor model where a broad and well-diversified country index return is the dependent variable. Indeed, we argue that a country is perfectly integrated if the country-specific variance is zero after controlling for global factors; market indexes from two perfectly integrated countries would, of course, have zero residual covariance.

We do not argue with BHZ's contention that if residual variances (and covariances) are zero, then increased comovement can come only from increased factor exposures (betas) or increased factor volatility. But we do contend that two countries can become more integrated over time even if factor exposures or factor volatilities decrease rather than increase, as long as country-specific residual volatility is not zero.

BHZ recognize that residual volatility plays a role. They observe that, "Correlations are increasing in betas and factor volatilities, but they are decreasing in idiosyncratic volatility, everything else equal," (pp. 7–8). At a later point, they state, "…return correlations across countries can increase because of increased betas with respect to common international factors, increased factor volatilities, or a decrease in idiosyncratic volatilities," (p. 21), but one sentence later they say, "Because factor volatilities show no long term trend, permanent changes in correlation induced by globalization must come through betas." We believe that permanent changes in correlation can also be driven by reductions in country-specific (i.e., "idiosyncratic volatility").

As an example, consider two countries exposed to a global factor such as energy. In an earlier period of imperfect integration, suppose that the broad market indexes for these two countries were driven also by country-specific factors (unrelated across the two countries). Now imagine a later period when these countries are better integrated and country-specific factors are much less volatile, leaving the global energy factor to explain most of both countries' returns. Finally, assume that the energy factor's volatility is lower and that both countries' exposures to the energy factor are also smaller for structural reasons.[6] It is fairly easy to see that the correlation between the two countries' market returns could still *increase* from the earlier to the later period. Indeed, given a single global factor, the correlation between the two countries would become perfect if country-specific volatility vanished entirely, despite a decline in factor exposures and volatility.

It is easy to concoct more general examples to illustrate correlation can go in either direction when factor exposures or factor volatilities change between two periods; it depends on the change in residual (i.e., country-specific) volatility. If residual volatility is held constant, then a reduction in factor exposures or in factor volatility will often result in lower correlations, but even this depends on the sign of the factor exposures (and these can differ between, say, energy-importing and energy-exporting countries).

To illustrate these various possibilities, Table 1 presents three examples using a global two-factor model and two countries, *A* and *B*. In examples #1 and #2, there is a decrease in factor volatilities from period 1 to period 2, decreases in the values of all factor exposures, and decreases in residual volatility. For country *A*, residual volatility decreases from period 1 to period 2 by the same amount in both examples while the decrease in residual volatility for country *B* is larger in example #2. The return correlation between the two countries decreases in example #1, which is compatible with BHZ (2008). But despite decreases in factor and residual volatilities and in exposures, the correlation actually increases in example #2. This illustrates that simple correlation need not move in the same direction as exposures and factor volatilities, provided that residual volatility also changes.

In example #3, the factor exposures and residual volatilities are held constant between the two periods but volatility decreases for both factors. Despite the decreases in factor volatilities, the correlation between the two countries actually increases. In contrast, the R-squares decline. This illustrates that reductions in factor

[5] E.g., they say, "Correlations are an important ingredient in the analysis of international diversification benefits and international financial market integration. Of course, correlations are not a perfect measure of either concept." (BHZ, 2008, p. 20).

[6] Because, for instance, both countries now produce less energy.

Table 1
Effects of changing factor exposures, factor volatility, and country-specific (residual) volatility on inter-country broad market index return correlations and the *R*-square measure of integration, two global factors and two countries, *A* and *B*.This table presents three examples using a global two-factor model and two countries, *A* and *B*. In examples #1 and #2, there is a decrease in factor volatilities from period 1 to period 2, decreases in the values of all factor exposures, and decreases in residual volatility. In example #3, the factor exposures and residual volatilities are held constant between the two periods but volatility decreases for both factors.

Time period	Factor 1 volatility	Factor 2 volatility	$Beta_1$		$Beta_2$		Country-specific volatility (residual volatility)		*R*-square		Correlation
			A	*B*	*A*	*B*	*A*	*B*	*A*	*B*	
Example #1, Decreased correlation with decreased factor exposures and volatility											
1	0.2	0.1	1	0.9	0.5	0.3	0.2	0.3	0.515	0.270	0.372
2	0.1	0.08	0.5	0.7	0.4	0.25	0.05	0.14891	0.585	0.193	0.322
Example #2, Increased correlation with decreased factor exposures and volatility											
1	0.2	0.1	1	0.9	0.5	0.3	0.2	0.3	0.515	0.270	0.372
2	0.1	0.08	0.5	0.7	0.4	0.25	0.05	0.10340	0.585	0.331	0.422
Example #3, Increased correlation with reduced factor volatility (ceteris paribus)											
1	0.2	0.2	1	0.9	0.5	−0.3	0.2	0.3	0.556	0.286	0.282
2	0.19	0.01	1	0.9	0.5	−0.3	0.2	0.3	0.475	0.245	0.341

volatility need not reduce correlations across countries and shows that the simple correlation and our *R*-square measure of integration can move in opposite directions.

4. Criticisms of the multi-factor *R*-square indicator of integration

Some authors have intimated that the *R*-square from a multi-factor model, the measure of integration we propose, is flawed because it will indicate a greater degree of integration during periods when factor volatilities happen to be high relative to total country volatility. The argument descends from Forbes and Rigobon (2002) who find larger cross-country correlation when common volatility is high; they contend that correlations are biased by heteroskedasticity.[7]

For example, Bekaert, Harvey, and Ng (2005) state, "For a given factor model, increased correlation is expected if the volatility of a factor increases." They focus on contagion, which they assess by changes in the cross-correlations of residuals from a factor model. Brooks and Del Negro (2004b) estimate that recent large IT shocks have induced larger correlations.

The force of these arguments is greater when they refer to the sampling error in volatility rather than to the true volatility. Abstracting from sampling error, it seems rather obvious that a country is financially well integrated when global factors really do explain the vast bulk of its returns. *Reductio ad absurdum*, if there is no unexplained variation at all (i.e., if the multi-factor *R*-square is truly 1.0), global influences account for everything. It is hard to imagine that this means anything other than perfect integration. Conversely, if local or regional influences explain all of a country's returns, the country is completely segmented financially for all practical purposes.

In between the two extremes, integration might not rise linearly with the multi-factor *R*-square, but the latter should still provide an acceptable and informative ordinal ranking. This remains the case even when the true variances of factors (and of residuals) change over time; there is no reason why market integration should be time invariant.

When sampling error is admitted, in either factor volatility or residual volatility, there will inevitably be some variation in the estimated *R*-square measure of market integration across different periods even when the true but unknown *R*-square is constant. When the true *R*-square is time varying, the estimated pattern of integration will display more variability than the true pattern. Consequently, it is only prudent to rely on longer-term trends as opposed to shorter-term variation in estimated integration.

When comparing integration among countries, sampling error in the global factors is not likely to be a serious problem. If the volatility of multi-factor country-specific residuals, such as $e(j,t)$ in model (1), is constant over time while there is considerable sampling variation in the factors, the ordinal ranking of integration across countries should be a reliable indicator for any given estimation period because the factor variation is common. Hence, the estimated *R*-squares will vary over time due to sampling error, but the variation will be strongly correlated across countries and inter-country rankings should be fairly reliable.

This is not true when the volatility of multi-factor residuals (non-global influences) is prone to estimation error. Even if the global factors display constant volatility across time, cross-country comparisons of estimated integration would be compromised by large and cross-sectionally unrelated sampling error in every country's residuals. Hence, in contrast to the suggestions in previous literature, it seems that sampling error in residual volatility is more problematic than sampling variation in

[7] Forbes and Rigobon credit Ronn (1998) with originating this idea, but Ronn credits a remark by Rob Stambaugh at a conference. See Forbes and Rigobon (2002, p. 2229 and footnote 8). The examples of the previous section show that such a conclusion is not always unassailable, but it probably is correct in many instances.

the global factors, at least for assessing which countries are more and less integrated.

Another conceptual problem with a multi-factor *R*-square measure of integration arises when empirically derived global factors are actually country specific. For example, suppose there are two countries and two estimated global factors but the exposures to the two factors are (1, 0) for country *A* and (0, 1) for country *B*. The adjusted *R*-squares could be very large, yet these two countries would be completely non-integrated because they are sensitive to disparate global shocks.[8] The same thing could apply by region; e.g., African countries being sensitive only to factor #2 and European countries sensitive only to factor #3.

Fortunately, this issue can be investigated empirically by simply examining estimated country exposures to derived global factors. If the pattern of exposures is something like the example of (1, 0) and (0, 1), then integration cannot be concluded even when the *R*-square is large. But if the exposures are well-distributed across the factors for all countries, then it would be valid to use the *R*-square as an indication of the degree of integration. We provide evidence about this issue in Section 12 on robustness checks below; see item #1 in that section.

5. Implications of the multi-factor *R*-square measure of integration

Global integration is intriguing for numerous reasons; witness the myriad of popular articles and books on globalization and its consequences. For investors though, the main reason for being interested in financial integration is its potential impact on diversification. Broad country indexes are not that well correlated, which might suggest that the benefits from diversification are particularly large on an international scale. A corollary is that diversification might be even better among developing markets since they generally display even smaller inter correlation.

We argue above that the correlation between broad country indexes is not a very good measure of integration. We believe it is also not a very good indicator of the benefits of diversification. But correlation is indeed a principal determinant of diversification, particularly for mean/variance optimizers, so how can such a contention be valid? The answer comes from recognizing that broad market index correlations cannot reveal the full extent of mean/variance optimization over individual assets.

To give an example, *reductio ad absurdum*, consider countries *A* and *B* that are perfectly integrated according to our *R*-square metric but whose broad market indexes are imperfectly correlated (because the *indexes*' factor exposures are not proportional). Provided there are sufficient numbers of individual assets within the two countries and that portfolios can be constructed freely, meaning that short positions are possible if necessary, a portfolio can be structured from country *B*'s individual assets to have factor exposures that exactly match the broad market index from country *A*.

If such a structured portfolio is well-diversified, it will be highly correlated with country *A*'s market index. Indeed, if perfect diversification could be achieved, the correlation would also be perfect. It follows that there is no benefit whatsoever from diversifying between these two countries even though their market indexes exhibit imperfect correlation. There might, however, be a pure arbitrage if the mean returns differed between country *A*'s market index and country *B*'s structured portfolio.

In reality, of course, countries' indexes do not have *R*-squares of 1.0 on global factors. There is some remaining country-specific volatility even when the indexes are very well-diversified. So, there is *some* benefit from diversifying away country-specific risk, but this benefit declines as the *R*-square increases. Consequently, the multi-factor *R*-square is also a better indicator of diversification benefits than the simple correlation between country index returns.

6. Data

After examining several alternative data sources, we concluded that DataStream, a division of Thomson Financial, provides stock market indexes for the most countries and longest time periods. For some countries, this database has several different indexes and we selected the index that appeared to have the broadest coverage of stocks within the country and the longest period of availability. Table 2 lists the countries, the time periods on the database (as of the collection date, February 9, 2008), the identity of the index for each country, and its DataStream mnemonic (which can be used to assess the same data by anyone who subscribes to DataStream).

The abbreviations "RI" and "PI" in the DataStream mnemonics column of Table 2 refer, respectively, to a total *R*eturn *I*ndex, which includes reinvested dividends, and a *P*rice *I*ndex, which does not include dividends. The former is preferable, of course, and was selected whenever possible, but total return indexes are not available for the majority (51 countries).

To alleviate exchange rate noise, local currency indexes should be translated into a common currency; such conversions represent a ubiquitous practice in empirical studies of international financial markets. Any common currency would suffice, so we selected the U.S. dollar. In Table 2's mnemonics column, the designation "~U$" indicates that the original local currency stock index was converted into U.S. dollars with the DataStream exchange rate conversion facility. A few indexes are already in U.S. dollars, so the conversion was unnecessary and the designation is absent.

The data are daily but a cursory examination of the numbers reveals that many daily values in the database are not truly market determined. For example, there is usually a value given for January 1, a holiday in most countries, but it is identical to the value given on the previous day. Most holidays are not common across

[8] We thank an anonymous referee for pointing out this difficulty.

Table 2

Country index sample periods and index identification.Eighty-two countries have index data availability from DataStream, a division of Thomson Financial. Some countries have several indexes and the index chosen has the longest period of data availability. All index values are converted into a common currency, the U.S. dollar. An index with the designation "RI" is a total return index (with reinvested dividends). The designation "PI" denotes a pure price index. A "usable" return is obtained from two index values that are either exactly one calendar day apart or fall on Friday and the following Monday. In addition, neither the beginning nor the ending index value in the return calculation can be identical to its immediately preceding index value; this eliminates all holidays, which vary across countries, and all days with stale prices.

Country	DataStream availability		Usable daily returns	Usable returns per year	Index identification	DataStream mnemonic
	Begins	Ends				
Argentina	2-August-93	8-February-08	3630	250.0	Argentina Merval—Price index (~U$)	ARGMERV(PI)~U$
Australia	1-January-73	8-February-08	9145	260.5	Australia-DS Market $—TOT Return IND	TOTMAU$(RI)
Austria	1-January-73	8-February-08	9005	256.5	Austria-DS Market—TOT Return IND (~U$)	TOTMKOE(RI)~U$
Bahrain	31-December-99	8-February-08	1202	148.3	Dow Jones Bahrain $—Price Index	DJBAHR$(PI)
Bangladesh	1-January-90	8-February-08	2987	165.0	Bangladesh SE All Share Price Index (~U$)	BDTALSH(PI)~U$
Belgium	1-January-73	8-February-08	9129	260.1	Belgium-DS Market—TOT Return IND (~U$)	TOTMKBG(RI)~U$
Botswana	29-December-95	8-February-08	2700	222.9	S&P/IFCF M Botswa0.—Price Index (~U$)	IFFMBOL(PI)~U$
Brazil	12-April-83	8-Febuary-08	6308	254.1	Brazil Bovespa—Price Index (~U$)	BRBOVES(PI)~U$
Bulgaria	20-October-00	8-February-08	1858	254.5	BSE Sofix—Price Index (~U$)	BSSOFIX(PI)~U$
Canada	1-January-69	8-February-08	9912	253.5	S&P/TSX Composite Index—TOT Return IND (~U$)	TTOCOMP(RI)~U$
Chile	23-November-90	8-February-08	4174	242.5	Chile General (IGPA)—Price Index (~U$)	IGPAGEN(PI)~U$
China	31-August-94	8-February-08	3276	243.7	Shenzhen SE Composite—Price Index	CHZCOMP(PI)~U$
Colombia	10-March-92	8-February-08	4140	260.1	Colombia-DS Market—TOT Return IND	TOTMKCB(RI)~U$
Côte d'Ivoire	29-December-95	8-February-08	263	21.7	S&P/IFCF M COTE D'IVOIRE—TOT Return IND (~U$)	IFFMCIL(RI)~U$
Croatia	2-January-97	8-February-08	2826	254.6	Croatia Crobex—Price Index (~U$)	CTCROBE(PI)~U$
Cyprus	3-September-04	8-February-08	879	256.2	Cyprus General—Price Index (~U$)	CYPMAPM(PI)~U$
Czech Republic	9-November-93	8-February-08	3138	220.2	Czech REP.—DS Non-financial—TOT Return IND (~U$)	TOTLICZ(RI)~U$
Denmark	31-December-69	8-February-08	9109	239.0	MSCI Denmark—TOT Return IND (~U$)	MSDNMKL(RI)~U$
Ecuador	2-August-93	8-February-08	2506	172.6	Ecuador ECU (U$)—Price Index	ECUECUI(PI)
Egypt	2-January-95	8-February-08	3344	255.3	Egypt Hermes Financial—Price Index (~U$)	EGHFINC(PI)~U$
Estonia	3-June-96	8-February-08	2979	255.0	OMX Tallinn (OMXT)—Price Index (~U$)	ESTALSE(PI)~U$
Finland	2-January-87	8-February-08	5389	255.4	OMX Helsinki (OMXH)—TOT Return IND (~U$)	HEXINDX(RI)~U$
France	1-January-73	8-February-08	9134	260.2	France-DS Market—TOT Return IND (~U$)	TOTMKFR(RI)~U$
Germany	1-January-65	8-February-08	10 883	252.5	DAX 30 Performance—TOT Return IND (~U$)	DAXINDX(RI)~U$
Ghana	29-December-95	8-February-08	2381	196.6	S&P/IFCF M GHA0.—Price Index (~U$)	IFFMGHL(PI)~U$
Greece	30-September-88	8-February-08	4953	255.9	Athex Composite—TOT Return IND (~U$)	GRAGENL(RI)~U$
Hong Kong	1-January-65	8-February-08	9641	223.7	Hang Seng—TOT Return IND (~U$)	HNGKNGI(RI)~U$
Hungary	2-January-91	8-February-08	4251	248.6	Budapest (BUX)—Price Index (~U$)	BUXINDX(PI)~U$
Iceland	31-December-92	8-February-08	3509	232.3	OMX Iceland All Share—Price Index (~U$)	ICEXALL(PI)~U$
India	2-January-87	8-February-08	5126	242.9	India BSE (1 0 0) National—Price Index (~U$)	IBOMBSE(PI)~U$
Indonesia	24-January-01	8-February-08	1821	258.7	Indonesia-DS Market—TOT Return IND	TOTMKID(RI)~U$
Ireland	1-January-73	8-February-08	9121	259.8	Ireland-DS Market $—TOT Return IND	TOTMIR$(RI)
Israel	23-April-87	8-February-08	5297	254.7	Israel TA 100—Price Index (~U$)	ISTA100(PI)~U$
Italy	1-January-73	8-February-08	9106	259.4	Italy-DS Market $—TOT Return IND	TOTMIT$(RI)
Jamaica	29-December-95	8-February-08	927	76.5	S&P/IFCF M Jamaica—Price Index (~U$)	IFFMJAL(PI)~U$
Japan	1-January-73	8-February-08	9049	257.8	Topix—TOT Return IND (~U$)	TOKYOSE(RI)~U$
Jordan	21-November-88	8-February-08	4840	251.9	Amman SE Financial Market—Price Index (~U$)	AMMANFM(PI)~U$

Table 2 (*continued*)

Country	DataStream availability		Usable daily returns	Usable returns per year	Index identification	DataStream mnemonic
	Begins	Ends				
Kenya	11-January-90	8-February-08	4272	236.3	Kenya Nairobi SE—Price Index (~U$)	NSEINDX(PI)~U$
Kuwait	28-December-94	8-February-08	3390	258.5	Kuwait KIC General—Price Index (~U$)	KWKICGN(PI)~U$
Latvia	3-January-00	8-February-08	2060	254.4	OMX Riga (OMXR)—TOT Return IND (~U$)	RIGSEIN(RI)~U$
Lebanon	31-January-00	8-February-08	0	0.0	S&P/IFCF M Lebanon—Price Index (~U$)	IFFMLEL(PI)~U$
Lithuania	31-December-99	8-February-08	1977	243.9	OMX Vilnius (OMXV)—TOT Return IND (~U$)	LNVILSE(RI)~U$
Luxembourg	2-January-92	8-February-08	4137	256.9	Luxemburg-DS Market—TOT Return IND (~U$)	LXTOTMK(RI)~U$
Malaysia	2-January-80	6-February-08	7032	250.3	KLCI Composite—Price Index (~U$)	KLPCOMP(PI)~U$
Malta	27-December-95	8-February-08	3094	255.3	Malta SE MSE—Price Index (~U$)	MALTAIX(PI)~U$
Mauritius	29-December-95	8-February-08	956	78.9	S&P/IFCF M Mauritius—Price Index (~U$)	IFFMMAL(PI)~U$
Mexico	4-January-88	8-February-08	5148	256.2	Mexico IPC (Bolsa)—Price Index (~U$)	MXIPC35(PI)~U$
Morocco	31-December-87	8-February-08	5125	254.9	Morocco SE CFG25—Price Index (~U$)	MDCFG25(PI)~U$
Namibia	31-January-00	8-February-08	1895	236.2	S&P/IFCF M Nambia—Price Index (~U$)	IFFMNAL(PI)~U$
Netherlands	1-January-73	8-February-08	9135	260.2	Netherland-DS Market—TOT Return IND (~U$)	TOTMKNL(RI)~U$
New Zealand	4-January-88	8-February-08	5220	259.8	New Zealand-DS Market $—TOT Return IND	TOTMNZ$(RI)
Nigeria	31-December-84	8-February-08	3035	131.4	S&P/IFCG D Nigeria—Price Index (~U$)	IFGDNGL(PI)~U$
Norway	2-January-80	8-February-08	7310	260.1	Norway-DS Market $—TOT Return IND	TOTMNW$(RI)
Oman	22-October-96	8-February-08	2875	254.5	Oman Muscat Securities Market—Price Index (~U$)	OMANMSM(PI)~U$
Pakistan	30-December-88	8-February-08	4468	233.8	Karachi SE 100—Price Index (~U$)	PKSE100(PI)~U$
Peru	2-January-91	8-February-08	4373	255.7	Lima SE General (IGBL)—Price Index (~U$)	PEGENRL(PI)~U$
Philippines	31-December-87	8-February-08	4916	244.5	Philippine SE I (PSEi)—Price Index (~U$)	PSECOMP(PI)~U$
Poland	16-April-91	8-February-08	4288	255.0	Warsaw General Index—Price Index (~U$)	POLWIGI(PI)~U$
Portugal	5-January-88	8-February-08	5127	255.2	Portugal PSI General—Price Index (~U$)	POPSIGN(PI)~U$
Romania	19-September-97	8-February-08	2650	255.1	Romania BET (L)—Price Index (~U$)	RMBETRL(PI)~U$
Russia	1-September-95	8-February-08	2900	233.2	Russia RTS Index—Price Index (~U$)	RSRTSIN(PI)~U$
Saudi Arabia	31-December-97	8-February-08	1820	180.1	S&P/IFCG D Saudi Arabia $—TOT Return IND	IFGDSB$(RI)
Singapore	1-January-73	8-February-08	8994	256.2	Singapore-DS Market EX TMT—Return IND (~U$)	TOTXTSG(RI)~U$
Slovakia	14-September-93	8-February-08	3461	240.3	Slovakia SAX 16—Price Index (~U$)	SXSAX16(PI)~U$
Slovenia	31-December-93	8-February-08	3620	256.6	Slovenian Exch. Stock (SBI)-Price Index (~U$)	SLOESBI(PI)~U$
South Africa	1-January-73	8-February-08	9143	260.5	South Africa-DS Market $—TOT Return IND	TOTMSA$(RI)
South Korea	31-December-74	8-February-08	7839	236.8	Korea SE Composite (KOSPI)—Price Index (~U$)	KORCOMP(PI)~U$
Spain	2-January-74	8-February-08	8589	251.9	Madrid SE General—Price Index (~U$)	MADRIDI(PI)~U$
Sri Lanka	5-September-90	8-February-08	3879	222.6	Colombo SE All Share—Price Index (~U$)	SRALLSH(PI)~U$
Sweden	28-December-79	8-February-08	7044	250.5	OMX Stockholm (OMXS)—Price Index (~U$)	SWSEALI(PI)~U$
Switzerland	1-January-73	8-February-08	9006	256.6	SWITZ-DS Market—TOT Return IND (~U$)	TOTMKSW(RI)~U$
Taiwan	31-December-84	6-February-08	5821	252.0	Taiwan SE Weighted—Price Index (~U$)	TAIWGHT(PI)~U$
Thailand	2-January-87	8-February-08	5491	260.2	Thailand-DS Market $- TOT Return IND	TOTMTH$(RI)
Trinidad	29-December-95	8-February-08	1620	133.7	S&P/IFCF M Trinidad & Tobago—Price Index (~U$)	IFFMTTL(PI)~U$

Table 2 (*continued*)

Country	DataStream availability		Usable daily returns	Usable returns per year	Index identification	DataStream mnemonic
	Begins	Ends				
Tunisia	31-December-97	8-February-08	2609	258.2	Tunisia Tunindex—Price Index (~U$)	TUTUNIN(PI)~U$
Turkey	4-January-88	8-February-08	5188	258.2	ISE TIOL 100—Price Index (~U$)	TRKISTB(PI)~U$
Ukraine	30-January-98	8-February-08	1606	160.2	S&P/IFCF M Ukraine—Price Index (~U$)	IFFMURL(PI)~U$
United Arab Emirates	1-June-05	8-February-08	595	221.3	MSCI UAE $—Price Index	MSUAEI$
United Kingdom	1-January-65	8-February-08	11 239	260.8	UK-DS Market $—TOT Return IND	TOTMUK$(RI)
United States	1-January-65	8-February-08	10 390	241.1	S&P 500 Composite—TOT Return IND (~U$)	S&PCOMP(RI)~U$
Venezuela	2-January-90	8-February-08	4685	258.8	Venezuela-DS Market $-TOT Return IND	TOTMVE$(RI)
Zimbabwe	6-April-88	8-February-08	2994	150.9	Zimbabwe Industrials—PI~U$	ZIMINDS(PI)

countries, but DataStream posts a value anyway, identical to the previous daily value for the holiday country but not, of course, for other countries. Using every posted index value to compute daily returns, sometimes false returns, would introduce spurious asynchroneity across countries. This could seriously bias downward any measure of market integration, the very item we are striving to estimate as precisely as possible.

Our resolution of this difficulty is simple. Given the large number of observations for most countries, we can afford to squander a few, even good ones, just to be safe. Hence, we discard any return unless it is computed from two index values that are either (a) exactly one calendar day apart or (b) exactly three days apart and fall on a Friday and the following Monday. No returns are retained if the two successive index values are two days apart or more than three days apart. Moreover, to be a valid return, neither the first index value (the return denominator) nor the second index value (the numerator) can be identical to its immediately preceding value. An identical value would indicate either a holiday or, in the case of smaller countries with infrequent trading, simply a stale value. This approach might expunge a few valid returns. For example, it is possible that two successive trading days could produce identical index values to five significant digits (and a return of zero) but this is improbable because indexes are composed of many stocks. Table 2 enumerates the retained "usable" values and their number per year for each country.

Some countries exhibit very sparse usable data. Côte d'Ivoire, for example, supposedly has data availability for more than 12 years, but only 263 daily observations are reliable, fewer than 22 observations per calendar year. For this country, the index value rarely changes more than once per week, so there are many stale values and any computed relation between such returns and valid returns from other countries would be unreliable. An even more extreme case is Lebanon, which does not have a single usable daily return during its more than eight years of "availability" on DataStream.

7. Estimating global factors with principal components

Given the data limitations described in the previous section, we approached the estimation of global factors with a considerable degree of trepidation. Although four countries were available as early as 1965 and two others (Canada and Denmark) appeared in 1969, only by early 1973 were enough countries available to have a sufficient cross-country sample. During 1973, 17 countries are present and the same 17 remain present every year thereafter. Among these 17, four are located in the East Asia/Austro-Pacific time zone region, two are in North America, and the other 11 are in the European zone (this includes South Africa).

The 17 countries present in 1973 are, of course, the largest economies and have the longest tradition of free capital mobility. Most observers would say they are clearly the most globally integrated. Consequently, we used these 17 countries, and only these 17, in estimating global factors. Hereafter, we refer to these countries as the "pre-1974 cohort."

For each calendar year from 1973 to 2006 inclusive, a covariance matrix was computed using dollar-denominated index returns for the 17 countries. Because of simultaneity considerations (holidays and stale prices), the number of daily return observations used in calculating the covariance matrix is somewhat less than the typical number of trading days per year. But in every year since the beginning of the 1980s, there are at least 200 daily observations; the largest number was 236 in calendar year 1995. In the 1970s, there were fewer simultaneous usable returns; the minimum was 163 in 1977.

Because of time zone differences, the covariance matrix was augmented by including the one-day lagged return from the North American countries, Canada, and the U.S. The rationale is straightforward. North America is the last region to trade on a given calendar day, so if something globally important happens after the Asian or European markets close but while North America is still

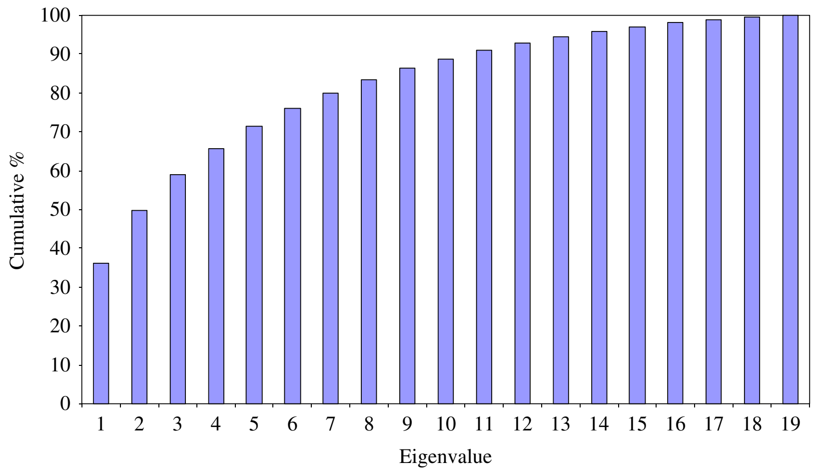

Fig. 2. Average cumulative percentage of variance explained by sorted eigenvalues, pre-1974 cohort covariance matrices, 1973–2006. The cumulative percentage of variance is explained within each estimation year by principal components extracted from the pre-1974 cohort of countries. Then the average percentage is taken over 34 sample years. The pre-1974 cohort consists of 17 countries that are present on DataStream in 1973 and remain present every year thereafter. For each calendar year from 1973 to 2006, a covariance matrix is computed using the dollar-denominated index returns for the 17 countries. Eigenvectors are computed and sorted from the largest to smallest eigenvalue. Then principal components are computed from eigenvector-weighted returns in the subsequent year.

open, there will be a non-simultaneity, a comovement between North American returns and other regions' returns on the next day. There could, of course, be some global shock after Asia is closed and Europe is still open, but since the North American markets will react to the same shock, parsimony suggests that only their lagged values be included.[9]

Once the eigenvectors are computed and sorted from the largest to smallest eigenvalue, principal components are estimated from returns in the subsequent calendar year. In other words, the weightings (eigenvectors) computed from the 1973 covariance matrix are applied to the returns of the same 17 countries during 1974. This is repeated in each calendar year; weightings from 1974 used with returns from 1975, and so on until the 2006 weightings are applied to the 2007 returns that comprise the final available full sample year. This produces 34 calendar years with out-of-sample principal components.[10]

As proxies for global factors, we decided to retain the first 10 principal components, which generally account for close to 90% of the cumulative eigenvalues (or, intuitively, 90% of the total volatility in the covariance matrix). The number of retained factors is admittedly somewhat arbitrary. It seemed reasonable that 10 large industry groupings adequately capture most global shocks. Even if something is omitted, it is omitted for all countries and might not have much impact on the pattern of relative measures of market integration. (Admittedly, there could be a relative bias if an omitted factor is singularly important for a particular country.)

Fig. 2 plots the average across 34 sample years of the cumulative percentage of variance explained within the estimation year by the principal components. As shown in the figure, the first principal component explains only about 37% of the variance and five principal components are required to explain just over 70%. This is clear evidence supporting the existence of multiple global factors, many more than just one. Fig. 3 plots the cumulative variance explained in each estimation year by the first 10 principal components. There is some variation year-by-year, of course, and there appears to be a slight upward trend over time, but the total hovers consistently around 90% throughout the sample of years.

One additional precautionary wrinkle was added to our global factor estimation procedure. For each member of the pre-1974 cohort of 17 countries, separate principal components were estimated for each country after it was excluded from the calculation. For example, when the subject country is Japan, the covariance matrix and principal components are computed only from concurrent daily returns for the 16 countries *other* than Japan plus lagged daily returns from the two North American countries. When Canada or the U.S. is the subject country, the other 16 countries are used in the calculations but there is only one lagged return, that for the U.S. or Canada, respectively.

Excluding countries in the manner just described is intended to avoid any suspicion that a country's return regressed on global factors is biased by that same country being heavily weighted in the principal components. This is real concern because heavy principal component weightings are generally assigned to highly volatile countries, a natural consequence of sorting from the largest to smallest eigenvalue. Otherwise, since countries other than those in the pre-1974 cohort are not used in computing the principal components, their explanatory

[9] Including lagged values from Europe would add 11 rows and columns to the covariance matrix.

[10] The resulting principal components are not exactly orthogonal (as they would be if the eigenvectors had been used as weightings for returns during the same year). We have verified, however, that the correlations are always quite modest, so multicollinearity is never a problem when the principal components are used as explanatory variables in regressions.

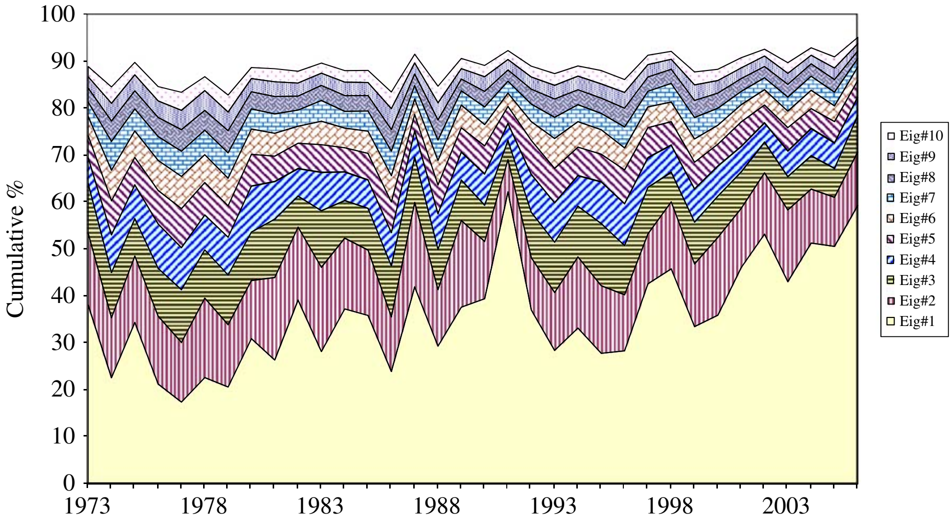

Fig. 3. Cumulative percentage of variance explained by sorted eigenvalues from pre-1974 cohort covariance matrices. The cumulative percentage of variance is explained in each estimation year by the first 10 global principal components. The pre-1974 cohort consists of 17 countries that are present in the DataStream in 1973 and remain present every year thereafter. For each calendar year from 1973 to 2006, a covariance matrix is computed using the dollar-denominated index returns for the 17 countries. Eigenvectors are computed and sorted from the largest to smallest eigenvalue. Then principal components are computed from eigenvector-weighted returns in the subsequent year.

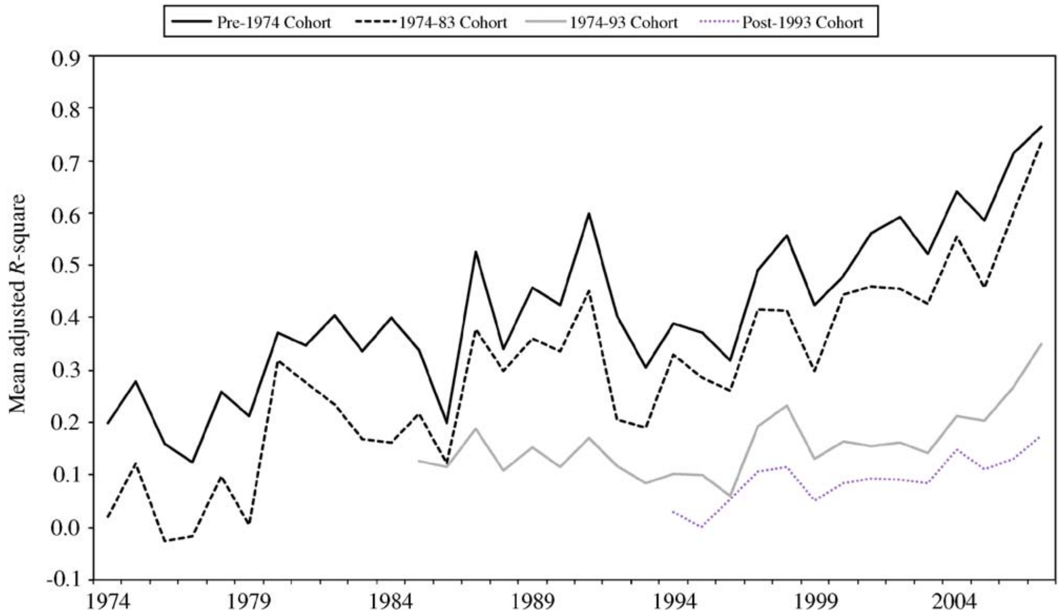

Fig. 4. Indicators of global market integration by country cohorts. Our measure of market integration is the adjusted R-square from a regression of country index returns on global factors. Plotted here are annual R-squares estimated for each individual country and then averaged across countries within each cohort. Provided that a country has at least 50 usable daily returns in a given calendar year, its dollar-denominated index returns for that year are regressed on 10 global factors, which are estimated by out-of-sample principal components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" present on DataStream in 1973 and remaining present every year thereafter. The "1974–1983," "1984–1993," and "post-1993" cohorts are composed of countries first appearing on DataStream during those decades.

power might have appeared relatively low, but this would have been an artifact.

The dimension of the covariance matrix thus varies slightly depending on which country's return is being regressed on the global factors. For countries other than the pre-1974 cohort, the covariance matrix is 19×19 (17 countries plus the two North American lags). For the non-North American members of the pre-1974 cohort, the covariance matrix is 18×18. For Canada and the U.S., it is 17×17. In all cases, only 10 principal components were retained for the subsequent year's regression.

8. Return regressions on global factors

The estimated global factors (out-of-sample principal components) serve as the common explanatory variable in a battery of regressions, one for each available country in each available calendar year. To enter a regression, the country must have at least 50 valid daily returns during the year. The adjusted *R*-square from these regressions is our suggested measure of market integration.

To condense the voluminous results, we assigned countries to four cohorts. The first cohort, pre-1974, has already been described above; it consists of 17 countries that were in the database by early 1973 or before. Other countries were assigned to three cohorts depending on when their data first became available. The 1974–1983 cohort consists of countries that appeared in that decade. The 1984–1993 cohort includes countries appearing in that decade and the post-1994 cohort includes all other countries. (The beginning dates of all countries are in Table 2.)

The main reason for categorizing countries into cohorts is to examine an average *R*-square across countries in a given calendar year, but countries appearing later in the data tend to start out with lower *R*-squares, so averaging all countries together as they appear would tend to depress any trend in the average. This is true to some extent even within each cohort, but the effect is less pronounced.

Fig. 4 shows the average *R*-square time pattern for the four cohorts. Three features are evident: (1) except for 1987–1994, each cohort displays a generally upward time trend; (2) countries that have been longer in the data, (i.e., older cohorts), have larger *R*-squares on average; and (3) movements in the average *R*-squares from one year to another are quite correlated across cohorts.

The generally upward trends displayed in Fig. 4 support the widely believed notion that global markets are becoming more integrated. From the beginning to the ending year for the first two cohorts, from 1974 to 2007, the integration enhancement has been substantial. The mean *R*-square for the pre-1974 cohort was only 0.198 in 1974 but it rose to 0.765 by 2007. A similar and somewhat greater percentage movement is exhibited by the 1974–1983 cohort, 0.021 in 1974 to 0.734 in 2007. The two later cohorts still have relatively low indicia of integration in 2007, but their improvement has been substantial since they first appeared in the data; *R*-squares rise from 0.125 to 0.349 (1984–1993 cohort) and from 0.027 to 0.175 (post-1993 cohort).

Table 3 buttresses this impression by regressing the *R*-squares for each country on a linear time trend during the years of data availability. For the 80 countries with a sufficient number of years to fit a linear time trend, 45 have positive *t*-statistics in excess of 2.0 and 17 others have positive time trends but lack significance (probably because there are not many yearly observations.) The mean time trend *t*-statistic is 2.53. We do not claim that these time trend fits are independent across countries, but there does seem to be a widely shared increase in market integration.

The European Community countries, which most would agree became much more integrated with each other during these 34 sample years, exhibit very strong time trends. France, Germany, Italy, the Netherlands, and Spain all have *t*-statistics in excess of eight. Some other notable increases in measured integration include South Korea (not surprisingly), Sweden, and the United Kingdom.

There are, however, some glaring exceptions to the general trend of enhanced integration. Four countries actually exhibit significantly *negative* time trends in their *R*-squares; Bangladesh, Jamaica, Jordan, and Malaysia. Jamaica has only six observations while Bangladesh and Malaysia might not be all that surprising,[11] but Jordan seems anomalous. Other countries with negative but

Table 3
Time trends for adjusted *R*-squares from global factor models.When a country has at least 50 usable daily returns in a given calendar year, its dollar-denominated index returns for that year are regressed on ten global factors, which have been estimated by out-of-sample principal components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" described in the text. The resulting *R*-squares for each country are then fit to a simple linear time trend for all available years. The number of available years and the *t*-statistics for the time trend slope coefficient are given below. Two countries, Côte d'Ivoire and Lebanon, are missing because they have too few years for a time trend to be fitted.

Country	Years	*t*-Statistic	Country	Years	*t*-Statistic
Argentina	15	1.13	Luxembourg	16	2.47
Australia	34	6.33	Malaysia	28	−2.32
Austria	34	2.45	Malta	12	−0.20
Bahrain	8	0.01	Mauritius	8	−0.93
Bangladesh	16	−3.17	Mexico	20	4.35
Belgium	34	6.53	Morocco	20	−0.24
Botswana	12	−0.11	Namibia	8	1.35
Brazil	25	6.43	Netherlands	34	8.50
Bulgaria	7	1.31	New Zealand	20	2.03
Canada	34	1.86	Nigeria	13	−1.40
Chile	17	3.01	Norway	28	3.69
China	14	1.24	Oman	11	1.71
Colombia	16	2.67	Pakistan	19	−0.72
Croatia	11	1.03	Peru	17	2.57
Cyprus	4	3.49	Philippines	20	2.30
Czech Republic	14	2.62	Poland	17	3.85
Denmark	34	4.08	Portugal	20	3.05
Ecuador	14	−0.40	Romania	11	1.67
Egypt	13	2.29	Russia	13	1.83
Estonia	12	3.26	Saudi Arabia	10	0.80
Finland	21	3.13	Singapore	34	3.61
France	34	8.78	Slovakia	15	3.97
Germany	34	8.50	Slovenia	14	2.08
Ghana	12	−1.31	South Africa	34	3.90
Greece	20	3.84	South Korea	33	7.66
Hong Kong	34	5.20	Spain	34	11.44
Hungary	17	3.22	Sri Lanka	18	−0.52
Iceland	15	1.89	Sweden	28	7.23
India	21	4.43	Switzerland	34	4.92
Indonesia	7	3.59	Taiwan	23	4.81
Ireland	34	4.09	Thailand	21	0.43
Israel	21	2.83	Trinidad	8	−0.52
Italy	34	8.53	Tunisia	10	0.55
Jamaica	6	−3.15	Turkey	20	3.54
Japan	34	3.45	Ukraine	10	−1.28
Jordan	19	−3.91	United Kingdom	34	7.82
Kenya	18	−0.83	United States	34	4.47
Kuwait	13	−1.69	United Arab Emirates	3	0.82
Latvia	8	5.31	Venezuela	18	0.13
Lithuania	8	1.89	Zimbabwe	14	−1.01

[11] Malaysia appears to be developing rapidly, but previous governments probably affected integration by imposing sanctions against exchange rate trading and blaming foreign investors for internal problems.

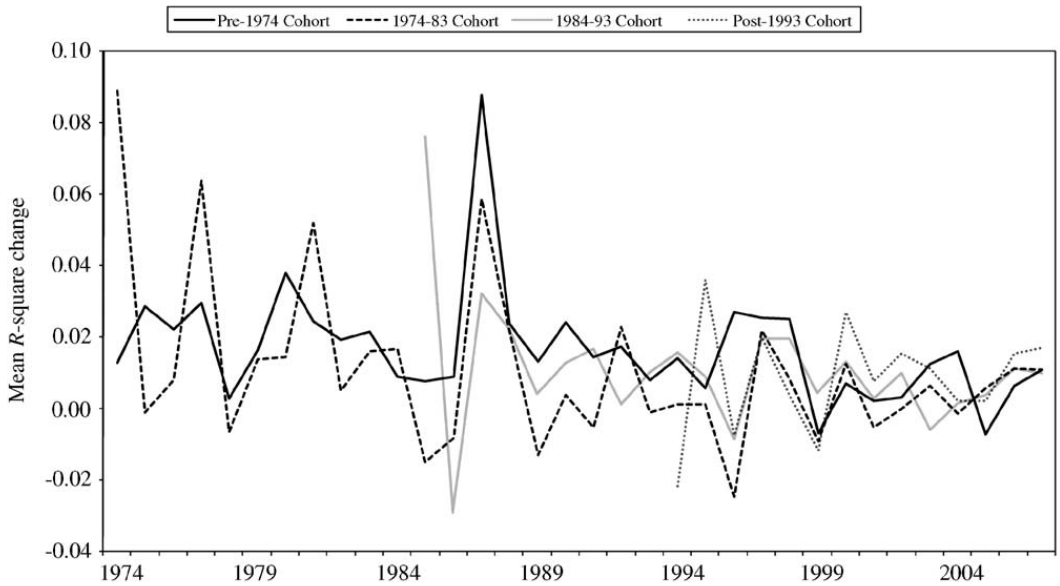

Fig. 5. Change in measured global market integration from supplementing contemporaneous global factors with two daily lagged factors. The *change* in mean *R*-square is derived from adding two daily lags to contemporaneous global factors. Provided that a country has at least 50 usable daily returns in a given calendar year, its dollar-denominated index returns for that year are regressed on 10 global factors plus two daily lags of each factor. The factors are estimated by out-of-sample principal components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" present on DataStream in 1973 and remaining present every year thereafter. The "1974–1983," "1984–1993," and "post-1993" cohorts are composed of countries first appearing on DataStream during those decades.

insignificant trends include Ghana, Nigeria, Pakistan, Sri Lanka, and Zimbabwe, which are definitely *not* surprises, given their troubles.

9. Checking for additional stale observations

As described above, we have taken certain precautions against using stale observations, which might serve to reduce the estimated degree of market integration. It is well known, however, that stock market indexes can be partially stale because some stocks do not trade every day. This induces positive serial correlation in index returns but also reduces contemporaneous comovement with global factors (presuming that the latter are derived, as they are here, from the most liquid markets).

To check for such a possibility, we repeated all the regressions for daily index returns while including not only contemporaneous global factors but also two daily lags of global factors. If there is a problem in some countries with infrequent trading, the adjusted explanatory power in these new regressions should be materially larger than when contemporaneous factors alone are employed.

The results are plotted in Fig. 5, which is a companion to Fig. 4, showing results over time for four country cohorts. Each value plotted in Fig. 5 is the adjusted *R*-square *difference* between a regression with contemporaneous plus two daily lags of factors and a regression with contemporaneous factors only. The former regressions have 30 explanatory variables (10 factors plus two daily lags of the same 10) while the latter have only 10.

Naturally, there is some variation, but several general features are apparent: (1) the *R*-square difference is positive on average but rather small, suggesting that the stale pricing problem, though present, is nothing much to worry about; (2) there is a slight downward trend over time, probably indicating a modest reduction in stale pricing and more frequent trading of constituent stocks; and, most important (3), there is not much difference across country cohorts. This last finding surprised us. We thought there would be more stale pricing in the recent cohorts because they are generally composed of smaller markets, yet there is no such evidence at all. Toward the end of the sample, the measures of market integration reported earlier in Fig. 4 might be slightly biased downward, by roughly 1%, but the relative rankings by cohort are almost completely unaffected.

10. The contrast with simple correlations as measures of integration

The same return data can be used to examine whether the measured pattern of market integration would have been different if simple bivariate correlations among countries had been employed instead of multi-factor *R*-squares. Fig. 6 reports simple correlation means by year and cohort. For each country, a correlation was computed between that country and every other country with at least 50 daily returns during each calendar year. Then, the correlations were averaged across countries within each cohort.

In Fig. 6, the increase in measured integration is substantially attenuated relative to Fig. 4 and integration reaches a lower absolute level in the latest year. There is an upward movement during the last few years and in the 1970s, but very little from 1980 to 2000. Over the entire 34 sample years, simple correlations do indicate enhanced integration on average, but the measured effect is smaller than that revealed by multi-factor *R*-squares. Thirty-nine countries exhibit significant upward time trends in the

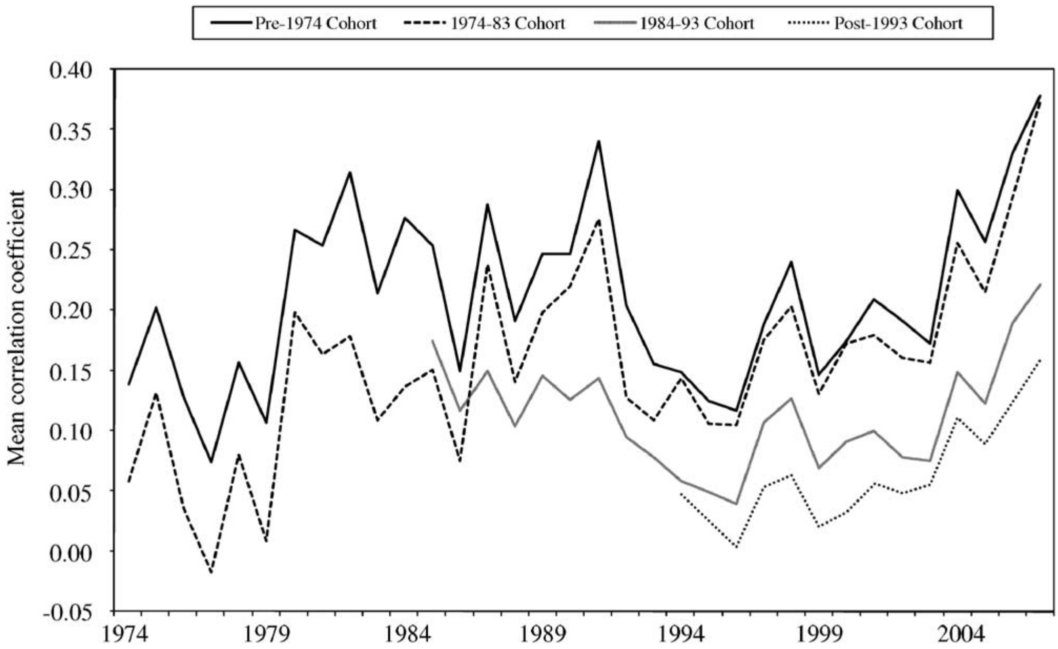

Fig. 6. Simple average correlations by country cohort and year. For each country, a correlation is computed between that country and every other country with at least 50 daily returns during each calendar year. The correlations are averaged across countries within each cohort. The "pre-1974 cohort" is present on DataStream in 1973 and remains present every year thereafter. The "1974–1983," "1984–1993," and "post-1993" cohorts are composed of countries first appearing on DataStream during those decades.

average simple correlation but 26 have negative trends; the mean t-statistic for the time trend coefficient is 1.90.[12] We conclude that simple correlations are not only theoretically inadequate but also provide an imperfect and biased downward empirical depiction of actual market integration.

11. Measured integration in bull and bear markets

Several previous authors have noticed that there is a tendency for international markets to be more correlated during downturns (bear markets) than during upswings (bull markets); e.g., see Longin and Solnik (2001). There seems to be no agreement, however, on whether this is simply statistical sampling error or something more fundamental; see Solnik and McLeavey (2008, pp. 416–417) for an analysis of this dispute. This is an important issue for international investing because if true correlations really are algebraically larger during bear markets, diversification is weaker just when it is most needed.

The possible increase in cross-country correlations during bear markets relative to bull markets made us curious about whether our suggested measure of integration also displayed a similar pattern. If market integration does not appear sensitive to market ups and downs, perhaps the above-mentioned pattern in correlations really is a statistical artifact. After all, integration rather than simple correlation provides a better depiction of the true benefits from international diversification.

So, we recomputed the adjusted R-squares from the global multi-factor model for each country after separating the country's returns into two groups by sign, i.e., positive return observations in one subsample and negative return observations in the other. Fig. 7 plots the R-square differences, bear market less bull market, by country cohort. Estimated R-squares are indeed slightly higher in bear markets. From the oldest to youngest cohort, the R-square mean differences over all available sample years are 0.061, 0.059, 0.041, and 0.030, respectively. There also appears to be a slight upward trend, which, if not an aberration, seems to imply larger differences between bear and bull markets in later years when the absolute level of integration is higher.

There is also evidence in Fig. 7 that particularly volatile markets, especially down markets, lead to unusually high estimates of integration. For example, the single largest difference between bull and bear market R-squares, over 0.3, occurs in 1987, the year of the large crash in October that struck most markets around the world. It is not clear, however, that this reveals anything other than sampling variation in statistical estimation. With hindsight, sample periods that are known to contain the largest amount of common volatility across countries are bound to display larger values of estimated integration.

12. A battery of robustness checks[13]

1. The first check involves whether the factors derived from principal components are truly global or, to the contrary, are country-specific (analogous to the example

[12] For space considerations, the time trends in simple correlations are not reported for each country but are available from the authors upon request.

[13] We thank an anonymous referee for asking questions that elicited the information in this section.

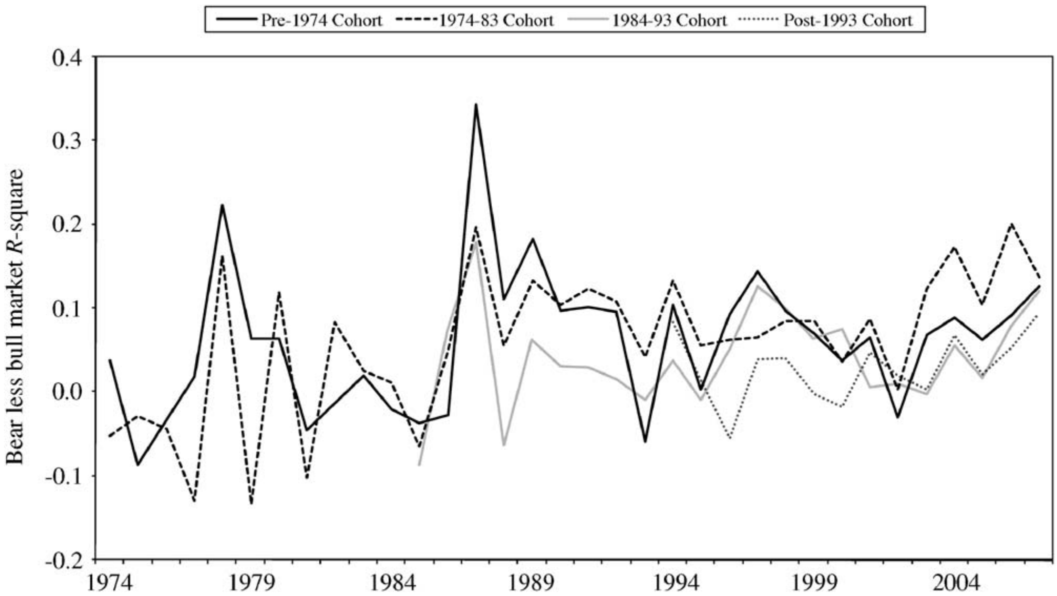

Fig. 7. Difference in measured global market integration between bear and bull markets. A country's returns are separated into two groups by sign, i.e., positive return observations in one sub-sample and negative return observations in the other. *R*-square differences, bear market less bull market are plotted below by country cohort. Provided that a country has at least 50 usable daily returns in a given calendar year, its dollar-denominated index returns for that year are regressed on 10 global factors, which are estimated by out-of-sample principal components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" present on DataStream in 1973 and remaining present every year thereafter. The "1974–1983," "1984–1993," and "post-1993" cohorts are composed of countries first appearing on DataStream during those decades.

mentioned above in Section 4). To provide evidence about this issue, we examine the pattern of exposures across countries to the 10 derived factors. These are the estimated slope coefficients obtained each calendar year for each country with available data in that year.

For the first factor, the principal component with the highest volatility, these exposures are positive in nearly 90% of all country years. Only five countries have negative average loadings on factor #1 (Mauritius, Nigeria, Saudi Arabia, Ukraine, and the United Arab Emirates), and these countries have relatively short periods of data availability (see Table 2). Splitting the globe into six regions (Africa, Americas, Asia, Europe, Middle East, and Pacific), we find that all regions have positive average exposures to factor #1. Thus, the first principal component appears to be proxying for a world factor that applies to all but a handful of small (and poorly integrated) countries.

Higher-order factors are more difficult to evaluate because principal components are mutually orthogonal by construction. Since most countries have positive exposures to the first factor, exposures to the other factors are unlikely to be mostly positive. However, based on three separate pieces of evidence, they are still rather dispersed internationally. First, across the six regions mentioned above, a majority of factors have the same average signs. Second, a Herfindahl index of concentration indicates that the absolute exposures are very dispersed and not at all concentrated (see Table 4). Third, cluster analysis of the exposures reveals that most countries occupy clusters that are quite close to each other in terms of Euclidean distance; moreover, the clusters themselves are geographically diverse. For example, Brazil is clustered with Bulgaria, Indonesia, and Poland.

Table 4
Herfindahl concentration measures for factor loadings.One possible concern is that a country might have a high multi-factor *R*-square (our suggested measure of integration) but is highly concentrated in one or a few factors. To illustrate an extreme case, suppose there are just two global factors and countries *A* and *B* have very high *R*-squares, but that factor loadings are $(1,0)$ for country *A* and $(0,1)$ for country *B*. This would indicate complete concentration in factor 1 (2) for country *A* (*B*), so they would not really be all that integrated. Alternatively, if the factor loadings were, say, $(\frac{1}{2},\frac{1}{2})$ for both *A* and *B* and the *R*-squares were high, they *would* be well integrated. An indication of the degree of concentration can be obtained for the factor exposures by first taking their absolute values and then computing a Herfindahl index from the resulting absolute values. Denoting by $\bar{b}_{i,j}$ the mean (over time) exposure to factor j for country i, we first take the sum of absolute values, $S_j=\sum_{i=1}^{N}|\bar{b}_{i,j}|$, over the $N=81$ available countries and then compute the fraction represented by country i, $s_{i,j}=|\bar{b}_{i,j}|/S_j$. The standard Herfindahl index is simply $H_j=\sum_{i=1}^{N_i}s_{i,j,t}^2$. The adjusted percentage Herfindahl index, which lies between zero and 100%, is given by

$$H_j^*=100(H_j-1/N)/(1-1/N).$$

The resulting H^*'s (in percent) from left to right for factors 1–10, are as follows:

0.629	2.226	1.480	2.536	2.150	1.927	2.373	3.876	4.841	1.653

Since H^* can vary between zero and 100%, every estimated H^* above is close to the low end of the possible range, thereby indicating that no factor is concentrated in a few countries. All factors have exposures that are diversely spread across countries.

Complete details of the results summarized above and of all results in this robustness checks section are available in an unpublished addendum from the authors.

2. Another issue is whether principal components are really needed. Instead, could we have used as global

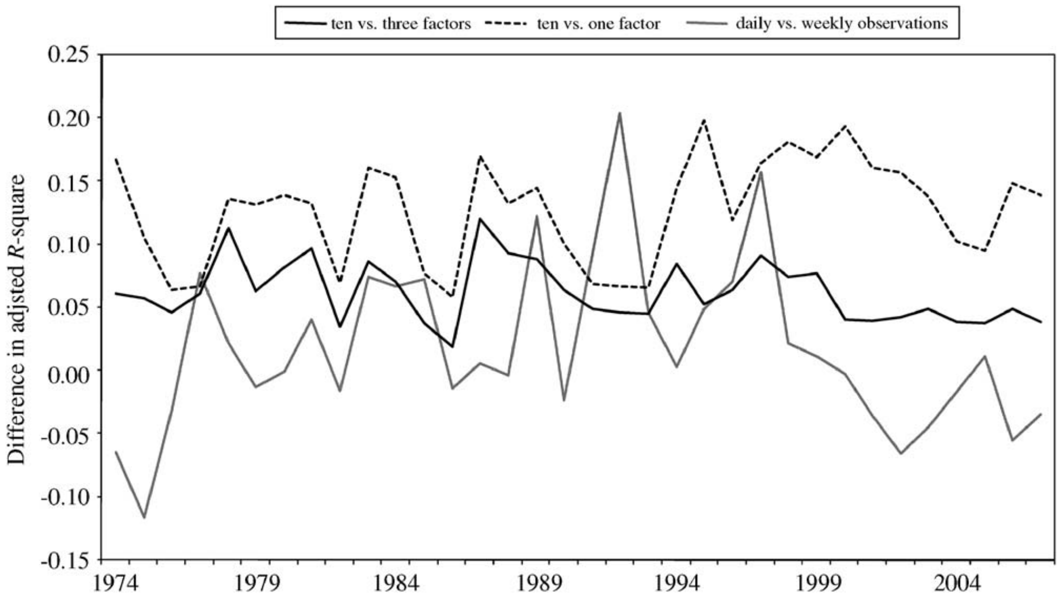

Fig. 8. Comparing the number of factors and the data frequency, pre-1974 cohort. The differences in adjusted *R*-square are derived by comparing 10 versus 3 factors, 10 versus 1 factor, and daily versus weekly observations (with 10 factors). Provided that a country has at least 50 usable daily returns in a given calendar year, its dollar-denominated index returns for that year are regressed on global factors, which are estimated by out-of-sample principal components based on the covariance matrix in the previous calendar year computed with the returns from 17 major countries, the "pre-1974 cohort" present on DataStream in 1973 and remaining present every year thereafter.

factors the market index returns from 10 large countries? Principal components do have the advantage of mutual orthogonality, unlike large market indexes, but that might be only a minor convenience and using widely available market indexes would save a lot of trouble.

So, we picked the 10 largest markets and repeated the entire analysis. Details will be provided upon request but the bottom line is that the results are hardly distinguishable. To our surprise, 10 large market indexes provide almost the same pattern of growing integration over time for each of the country cohorts as we have seen earlier based on principal components. The pattern of growing market integration over time is evidently quite robust to the choice of factors.

Perhaps this should have been anticipated since there is an infinite number of well-diversified portfolios that span the same underlying pervasive influences.

3. Do we really need 10 factors or would fewer have sufficed? We decided to recompute the adjusted *R*-squares, our measure of market integration, using just the first three of the 10 principal component factors and then just the first factor alone. Using three factors instead of 10 produces a similar result with respect to growing market integration but the adjusted *R*-squares are slightly lower throughout (by 5–10%, see Fig. 8).[14] This seems to suggest that factors 4–10 are indeed contributing something to the measured level of integration.

Using just a single factor, rather than three or 10, still provides a similar pattern of growing integration, but the *R*-square levels are reduced in every calendar year and in some years by more than 15% as seen in Fig. 8. We conclude that a single global market factor such as the first principal component is not able to fully capture the extent of market integration.

4. In attempting to control for thin trading and generally illiquid markets, we used two daily lags of the factors (see Fig. 5 and Section 9). An important issue is whether two lags are sufficient, particularly for the smaller and newer markets. To check this, we recomputed everything with five lags instead of two. However, we did this only with the first three factors because using all 10 would have substantially reduced the degrees of freedom. With 10 contemporaneous factors plus five daily lags of them all, there would have been 60 explanatory variables. We previously had required only 50 daily observations to compute the *R*-square for a country in a given calendar year, so we would have lost a few country years from the sample if we had used 10 factors and five lags.

The results with five lags are virtually indistinguishable from the results with two lags, so we feel safe in concluding that two lags produce reliable *R*-squares even for relatively illiquid markets.

5. We next investigated whether results obtained with daily observations would be altered if lower frequency observations were used instead. There are reasons (thin trading and other microstructure effects) to think that longer return intervals might be better even though the number of observations would be reduced. Using weekly observations rather than daily observations, we find a very similar pattern for the *R*-square measures of integrations. Daily observations produce slightly higher *R*-squares on average than weekly observations, but the pattern is reversed in the earliest and latest years. The daily–weekly difference in *R*-squares each year is depicted in Fig. 8 for the pre-1974 cohort.[15]

[14] To avoid unnecessary clutter, Fig. 8 contains results for the pre-1974 cohort only; the other cohorts display very similar patterns.

[15] Other cohorts show a similar pattern.

With weekly returns, there are at most 52 observations in a given calendar year and many countries are missing some data, so the average number of observations is even smaller. This means that we could not realistically hope to recompute the results for even longer intervals, say biweekly or monthly. But, since the weekly data provide such comparable results to the daily data, it seems safe to retain the general conclusion about growing integration.

6. We used adjusted R-squares as measures of integrations but we compared their pattern over time with the patterns of simple bi-country correlation coefficients in Fig. 6. The R-squares show a substantially larger increase over time than the simple correlations. Could this be attributable to the fact that the latter are not squared? We did not think this could be the case, but to be sure, we recomputed a comparable set of calculations to those depicted in Fig. 6 but after first squaring each simple correlation in each calendar year. Not surprisingly, the general level of squared correlations is smaller than the non-squared correlations, but the pattern over time is quite similar; i.e., there is not nearly as much indication of growing market integration from the squared simple correlations as from the multi-factor adjusted R-squares.

7. Above, in Section 4 on criticisms of the multi-factor R-square, we discussed the argument that larger absolute returns on explanatory factors might lead to an inference of greater integration. We do not think this argument is sound, for reasons given there, but it would nonetheless be interesting to ascertain whether the factors used here actually displayed larger absolute returns from the beginning to the end of our 33 calendar years.

To investigate this issue, we first calculated, for each calendar year, the standard deviation of returns for each of the 10 factors, their return kurtosis, and their sample range. Plotting these statistics reveals little evidence of any trend in kurtosis or range, but the first factor's standard deviation seems to be trending upward moderately. In contrast, some of the higher-order factors' standard deviations seem to be trending downward moderately. This is, perhaps, to be expected because Fig. 3 shows that the percentage of volatility explained by the first factor has risen over time while the total variance explained by the first 10 factors has been fairly stable at around 90%.

Next we fitted trend lines to these statistics in order to ascertain whether any trend is significant. For the standard deviation of factor #1, the upward trend is significantly positive while for some of the higher-order factors, it is significantly negative. We then asked whether the observed trend in the first factor's volatility *alone* could have been adequate to explain the observed increase in adjusted R-square over time.

To make this calculation, we simply assumed that the residual variance in each calendar year's regression was constant and only the volatility of the first factor increased. Using the fitted trend line, we estimated that the R-square for the pre-1974 cohort could have increased from 0.3 to a bit over 0.4 simply because the first factor's volatility grew. The actual observed increase was from 0.2 to 0.8, a considerably larger change than could have been induced by the observed rise in the first factor's standard deviation. Moreover, this calculation ignores the decreases in volatility displayed by higher-order factors, so we conclude that the observed change in estimated market integration could not have been caused by larger absolute returns later in the sample of calendar years.

Again, all details of these calculations can be obtained upon request from the authors.

13. Conclusions

Whenever there are multiple global factors, either priced APT-type factors or industry factors, the simple correlation between broad financial market index returns from two countries can be a poor measure of their economic integration. No convoluted theory is required to explain this fact; it is very simple. Unless the two country indexes have identical exposure profiles to the global factors, i.e., unless the response coefficients ("betas") for one country are all exactly proportional to the coefficients of the other country, their correlation will be imperfect even when the global factors explain 100% of the index returns in *both* countries.

If the index returns of two countries were explained perfectly by the same set of global factors, it seems sensible and intuitive to conclude that they are perfectly integrated. Hence, the explained variance from country stock market index returns regressed against common global factors represents a good measure of integration.

To provide some empirical evidence, we use daily stock market index returns for 34 years, 1973–2006 inclusive, to estimate out-of-sample global factors each calendar year during 1974–2007, taking care to avoid asynchroneity induced by time zone differences, holidays, and stale prices. Then, for 81 countries, we regress dollar-denominated daily market index returns on the derived global factors during each calendar year. The time pattern of adjusted R-squares from these regressions depicts the recent evolution of financial market integration.

There is strong evidence of growing integration for most countries. In the cohort of 17 larger countries that have been longest in the database, the average measure of integration (the mean adjusted R-square) rose from 0.198 in 1974 to 0.765 in 2007. Indeed, all country cohorts (defined by the decade when the country's data first became available), have experienced substantially increased integration over time, though the more recent a country's appearance in the database, the smaller its measured integration thus far. Simple correlations, however, give a different picture; they fail to reveal the full extent of integration over the past 30+ years.

Integration has grown faster in some countries than in others. Members of the European Community, plus a few others such as South Korea, have experienced the largest increases in measured integration. In contrast, several countries have gone in the opposite direction, toward less integration; these include such troubled nations as Bangladesh, Nigeria, Pakistan, Sri Lanka, and Zimbabwe.

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