Dispersion, Equity Returns Correlations and Market Integration

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Abstract

We propose two simple nonparametric measures of time-varying market integration and correlation, based on cross-sectional and time-series return data over short horizons. We investigate how global cross-market linkages evolve over time for 24 developed and 26 emerging markets from 1973 to 2005. We find that comovements between developed markets display upward time trends. In contrast, comovements between emerging markets do not. While global factors have supplanted regional factors as drivers for emerging market returns, the impact of local factors has not diminished. Hence, the degree of integration of emerging markets, measured as the fraction of total risk due to global factors, has not increased.

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1 Introduction

There is wide agreement among finance practitioners and academics that the benefits from international diversification can be substantial and stem from imperfect cross-country correlations (e.g. Lessard, 1973, and Solnik, 1974) and that cross-country correlations are time-varying (e.g. Kaplanis, 1988, Longin and Solnik, 1995, Goetzmann, Li and Rouwenhorst, 2005). However, whether cross-country correlations increase over time, remains widely debated.[1] Underpinning the interest in this issue are the related questions of whether the degree of international market integration is changing and whether global rather than local shocks are becoming the dominant drivers of national equity markets. While increased integration may lead to increased correlations between markets, making inferences about market integration on the basis of changes in cross-country correlations alone may be hazardous (see, e.g. Forbes and Rigobon, 2002). Hence, a separate measure of market integration is required. In this paper, we propose two novel non-parametric measures of monthly correlations and integration that we use to investigate how global stock market linkages evolve over time. Whereas most papers on cross-country correlations focus on developed markets and papers on market integration typically examine emerging markets, we investigate both measures for a broad global sample of 24 developed and 26 emerging markets. We analyze time trends in cross-country and cross-regional correlations and time trends in market integration for these 50 countries from 1973 to 2005.

First, we show that comovements between developed markets have increased significantly over the last few decades, while this is clearly not the case for emerging markets. We detect significant positive time trends in cross-country correlations for developed markets in both Europe and the Asia-Pacific area. During the last 32 years the average levels of cross-country correlations in these two regions have increased by 0.63 and 0.33 percent per annum respectively. For North America, the trend coefficient, while positive, is not significant. Moreover, the cross-regional correlations (average and pairwise) between developed market regions have significantly increased as well. This suggests that the benefits of international diversification strategies across developed markets, within or across regions may have decreased over time. In sharp contrast, for emerging markets, we do not detect any significant time trends in cross-country correlations in Eastern Europe, nor in the Asian and Latin American emerging markets. Moreover we find that Middle Eastern and African markets have even become significantly less correlated over the last decade, with average correlations

[1] For instance, Longin and Solnik (1995), Goetzmann, Li and Rouwenhorst (2005) and Baur (2006) report an increase in cross-country correlations between developed equity markets in recent decades. On the other hand, Bekaert et al. (2005) only report significant increases in correlations between European equity markets, but not for North America and the Far East. Also, King, Sentana and Wadhwani (1994) do not find evidence of increasing cross-country correlations either.

decreasing at a rate of -0.50 percent per year. Correlations between the emerging market regions do not display time trends either.

Second, we show that whereas developed markets in Europe and Asia Pacific are becoming increasingly integrated within world markets, the changes in the impact of global, regional and local factors on emerging markets returns are more subtle. In developed markets, the impact of global factors on equity market returns volatility has increased while that of both regional and local factors has receded. Using the fraction of an equity market's total volatility due to global factors as a yardstick for market integration, we document a significant upward trend in the degree of integration measures across developed markets. In developing economies, we find that, over the last decade, while global factors have supplanted regional factors as drivers of emerging markets comovements, the importance of country-specific factors has not diminished and the fraction of total equity market risk due to local factors has not decreased. Hence, while the aggregate degree of integration of emerging markets has not increased, it has taken a more global than regional nature over that time period.

Third, we examine whether different regions integrate into the world market at different speed. To the best of our knowledge, we are the first to formally test for this. Our results show that the developed European markets integrate faster into the world market than the Eastern European and Asia Pacific markets. However, the trends in the relative importance of global and regional factors are similar for these regions. This suggests that differences in the speed of integration are due to the changing importance of country-specific risk rather than due to changing relative importance of global and regional risk. The increasing relative importance of global factors seems to be a true global phenomenon, as it is present in five out of seven regions. However, only the markets that also have decreasing country-specific risk (developed European markets and Asia Pacific) are becoming more integrated into the world market.

We come to these findings as follows. We propose two new nonparametric measures for monthly time-varying correlations and market integration. Our approach starts with the notion that cross-sectional dispersion may be used to make inferences about correlations, as originally suggested by Solnik and Roulet (2000) and further developed by Baur (2006). The intuition is simple. If returns are highly correlated, then more often than not they will move together on the up side or on the down side inducing low cross-sectional dispersion. While correlations require a minimum sample length to be estimated with some precision, no such requirement is needed for cross-sectional dispersions, although the measure will be more imprecise if the number of returns entering the dispersion measure is small. Although the intuition is appealing, making inferences about correlations based purely on cross-sectional dispersion may be misleading in dynamic environments where returns volatility and exposure to common factors change over time.[2]

We show that in order to estimate time-varying correlations when both factor exposures and factor volatilities are time-varying, cross-sectional data alone is not sufficient, as it does not yield consistent estimates of instantaneous factor variance. In this case, we need to consider a time dimension in addition to the cross-section. Hence, we extend the methodology of Solnik and Roulet (2000) to directly estimate instantaneous cross-country correlations, under the assumption that national equity returns are subject to global and regional factors. We combine cross-sectional data with time series data over short horizons to derive a new nonparametric measure of instantaneous correlation based on cross-sectional dispersion and realized variance. Our measure can be interpreted as the average level of correlations of the assets under consideration. We treat the resulting time series of correlations as observable (in a fashion similar to e.g. Campbell *et al.*, 2001), which allows us to test for trends and breaks in a straightforward way.[3]

An alternative approach is to test the equality of unconditional correlation matrices across different periods (as in e.g. Kaplanis, 1988, and Goetzmann, Li and Rouwenhorst, 2005). However, this assumes constant correlations within the periods and testing for trends is not possible. Another alternative is to estimate correlations at each point in time, indirectly, based on a multivariate GARCH model (e.g. King, Sentana and Wadhwani, 1994, Longin and Solnik, 1995, De Santis and Gerard, 1997, Bekaert and Harvey, 1997) or directly, using the dynamic conditional correlation model of Cappiello, Engle and Sheppard (2003). As Kroner and Ng (1998) point out, the disadvantage of these parametric approaches is their computational intensity. Implementation even in relatively small cross-sections requires drastic simplifications in the specification of the time dependency and requires estimation of a large number of parameters.

In comparison, our nonparametric measure of instantaneous correlations has a number of important advantages. First, it is robust for monthly time variation in factor exposure and factor volatility, even though it does not require a specification of the factors. Second, estimating monthly correlations for a large cross-section requires very little computational effort. Furthermore, by treat-

[2] Indeed, this is a serious issue as the evidence of time variation in total returns and idiosyncratic volatility is ample and continuously growing (see for example Engle, 1982, Bollerslev, Chou and Kroner, 1992, Kroner and Ng, 1998, Campbell, Lettau, Malkiel and Xu, 2001). Furthermore, the degree of market integration is also time-varying (see e.g. Bekaert and Harvey, 1995, and Carrieri, Errunza and Hogan, 2005, Baele, 2005).

[3] Ferreira and Gama (2004) estimate monthly correlations between global industries and the world market index using realized covariances and variances. Even though they also use daily data to construct monthly correlation estimates, our approach is different. First, we explicitly assume a factor model and we estimate the average level of correlations within a group of assets, instead of bivariate correlations. Furthermore, our measure is based on the notion that cross-sectional dispersion and correlations are inversely related. Last, our correlation measure does not require the specification of the common factors. In the robustness check we examine a measure similar to Ferreira and Gama (2004).

ing the resulting time series as observable we can easily test for time trends in correlations and for structural breaks.

One could expect that increased cross-border economic and financial integration may lead to higher correlations between national equity and bond markets. However, cross-country correlations cannot be used directly to make inferences on market integration. One reason is that correlations might increase simply due to more volatile common factors, rather than to increased market linkages (see, e.g. Forbes and Rigobon, 2002). The literature provides a number of approaches to measuring time-varying market integration, which are typically based on either highly parametric models, on more detailed information on the securities, or on macro-economic data.[4] Moreover, only few of these papers explicitly estimate a time series of integration measures and formally test for time trends in market integration. In contrast, our approach is aimed to do precisely this. We measure market integration as the fraction of total risk due to global factors. This measure is bounded between zero and one and has a straightforward interpretation. In a segmented region, the local factors dominate and the integration measure is close to zero. On the other hand, a more integrated region is subject mainly to global risks and has an integration measure close to one. Although using this type of variance ratio as a measure of integration is not new (e.g. Bekaert and Harvey, 1997), our approach to estimating it is novel and delivers several benefits. We estimate the variance ratio based on a two-factor model and whereas our correlation measure does not require specification of the global and regional factors, specification of the two factors is required to estimate the integration measure. This allows us to estimate the integration measure nonparametrically using only daily return data over short horizons. This integration measure is easy to estimate on a (two-)monthly frequency and by regarding the resulting time series as observable we can test for trends and structural breaks. Furthermore, this allows us to examine how the variance decomposition into global, regional and country risk changes over time for the different regions.

While our simple correlation measure can be used to estimate a time series of the average level of comovements between national equity markets, it can also be of more practical use. Portfolio managers often need estimates of the instantaneous level of correlations. Typically, they base their estimates on past time series data over a longer period. However, by doing so, they actually assume that correlations are constant within the estimation period. Also, sufficiently long time

[4] For instance, Bekaert and Harvey (1995) model market integration parametrically, using a regime switching model. They measure integration as the conditional probability of being in the full integration state. Bekaert and Harvey (1997) use a dynamic factor model and consider, amongst others, the exposure with respect to the world factor to make inferences on market integration. On the other hand, De Jong and De Roon (2005) use the ratio of the market value of non-investable assets to the total market value of all assets as an indicator of the level of integration. Carrieri et al. (2005) propose the integration index, which is based on the fraction of the variance of non-investable assets that is not spanned by the investable assets.

series have to be available for all the assets under consideration. Conversely, our measure provides a direct estimate of the instantaneous average level of correlations by using only daily return data over very short periods. This is particularly useful for securities that do not have a long history yet. In addition, our measure of comovements is model-free. We assume certain return generating processes, but we do not specify any asset pricing model.

This paper is structured as follows. In the next section we use a simple model to formalize the intuition and derive the appropriate estimators for the average time-varying correlations, integration and their components. In Section 3 we describe the daily return data for the 50 national equity markets under consideration. Section 4 discusses the summary statistics of the estimated time series of correlations and integration measures. In Section 5 we discuss tests for stochastic and deterministic trends in these series. We also examine the presence of structural breaks and commonality of trends and we perform a robustness check analyzing monthly realized average pairwise correlations. Section 6 analyzes cross-regional correlations and Section 7 concludes.

2 Dispersion and comovements

2.1 Theoretical setup

This paper examines how global equity market comovements in developed and emerging markets evolve over time. To investigate these general market comovements we focus on average cross-country correlations (for different regions) rather than on pairwise cross-country correlations. Furthermore, we will test for time trends and structural breaks in the series of time-varying correlation estimates. In order to perform these tests we need sufficiently long time series of correlation estimates and return data for emerging markets typically becomes available only in the late eighties or early nineties. Therefore, we are interested in estimating correlations at a monthly frequency. In this section we propose a new measure for monthly average cross-country correlations within a certain region.

Consider country i of region a. We assume that equity returns follow a two-factor model. Formally,

$$\tilde{r}_{it} = \beta_{it}\tilde{W}_t + \gamma_{it}\tilde{L}_{at} + \tilde{\varepsilon}_{it}, \tag{1}$$

where $\tilde{r}_{it}$ is the return on country i's national index in excess of the risk free rate, β_{it} is the exposure at time t to the global factor $\tilde{W}_t$, γ_{it} is the exposure to the local factor $\tilde{L}_{at}$ and $\tilde{\varepsilon}_{it}$ is the country-specific idiosyncratic return. Brooks and Del Negro (2002) find that country factors have become less important within regions and regional factors dominate. Hence, we choose regional factors as local factors rather than country-specific factors. In this setup countries are fully integrated within the region. The country-specific return is the residual return component. Note that we do not derive an international asset pricing model. Rather, we assume a certain factor process driving international equity returns. We further assume the following distributional characteristics for the factors and idiosyncratic returns shocks:

$$\begin{aligned}\tilde{W}_t &\sim (\mu_{Wt}, \sigma^2_{Wt}) \\ \tilde{L}_{at} &\sim (0, \sigma^2_{Lat}) \\ \tilde{\varepsilon}_{it} &\sim (0, \sigma^2_{\varepsilon it}).\end{aligned}$$

Hence, the expected excess return for country i depends on the expectation of $\tilde{W}_t$ and the exposure to the global factor. The expected value of the global factor as well as all the variances are time-varying. We assume that the three components of equation (1), ($\tilde{W}_t$, $\tilde{L}_{at}$ and $\tilde{\varepsilon}_{it}$) are orthogonal. Also, the covariance matrix of the idiosyncratic country-specific returns of all countries within a certain region is assumed to be diagonal. Note that we do not assume normally distributed returns. Under this factor process, the return variance of any country i that belongs to region a can be expressed as follows:

$$\sigma^2_{it} = \beta^2_{it}\sigma^2_{Wt} + \gamma^2_{it}\sigma^2_{Lat} + \sigma^2_{\varepsilon it}. \tag{2}$$

Hence, the total variance of country i's returns can be decomposed in three parts: systematic variance due to world factors, systematic variance due to regional factors and country-specific residual variance. The covariance between countries i and j, both belonging to region a, is:

$$\sigma_{ijt} = \beta_{it}\beta_{jt}\sigma^2_{Wt} + \gamma_{it}\gamma_{jt}\sigma^2_{Lat}, \tag{3}$$

which leads to the following expression for the correlation between $\tilde{r}_{it}$ and $\tilde{r}_{jt}$, $i, j \in a$:

$$\rho_{ijt} = \frac{\beta_{it}\beta_{jt}\sigma^2_{Wt} + \gamma_{it}\gamma_{jt}\sigma^2_{Lat}}{\sqrt{\beta^2_{it}\sigma^2_{Wt} + \gamma^2_{it}\sigma^2_{Lat} + \sigma^2_{\varepsilon it}}\sqrt{\beta^2_{jt}\sigma^2_{Wt} + \gamma^2_{jt}\sigma^2_{Lat} + \sigma^2_{\varepsilon jt}}}. \tag{4}$$

In order to estimate this pairwise instantaneous correlation, we would have to estimate individual asset factor exposures and idiosyncratic variances. Our objective is to estimate monthly cross-country correlations, and it is a difficult task to estimate individual factor exposures and idiosyncratic variances reasonably accurately using 22 daily return observations within each month. Furthermore, this requires a specification of the common factors. We avoid this by assuming that, within each estimation interval, all countries within a region have identical factor exposures and idiosyncratic variances, i.e., $\beta_{it} = \beta_{at}$, $\gamma_{it} = \gamma_{at}$ and $\sigma^2_{\varepsilon it} = \sigma^2_{\varepsilon jt} = \sigma^2_{\varepsilon at}$ for all $i, j \in a$. Nevertheless, factor exposures differ across regions. Hence, while factor exposures and idiosyncratic volatility are restricted to be equal cross-sectionally within each region over each estimation period, we impose no restrictions on their variation across estimation intervals or across regions. Since our basic estimation interval is a month, they are allowed to vary at a monthly frequency. Under these assumptions, the excess returns on any country i in region a follows the following two-factor model:

$$\tilde{r}_{it} = \beta_{at}\tilde{W}_t + \gamma_{at}\tilde{L}_{at} + \tilde{\varepsilon}_{it}. \tag{5}$$

According to our model, on a given date individual country returns for a particular region differ in the cross-section only through the realization of their idiosyncratic country-specific return component. Country residual risk, defined as the idiosyncratic return variance $\sigma^2_{\varepsilon at}$, is the same for all countries within the region. We can now decompose total country variance into global variance, regional variance and country residual variance as follows:

$$\sigma^2_{at} = \beta^2_{at}\sigma^2_{Wt} + \gamma^2_{at}\sigma^2_{Lat} + \sigma^2_{\varepsilon at}. \tag{6}$$

Our assumptions imply that correlations are equal across all pairs of countries within a certain region. Hence $\rho_{ijt} = \rho_{klt} = \rho_{at}$ for all $i, j, k, l \in a$. Cross-country correlations within a certain region can be expressed as follows:

$$\begin{aligned} \rho_{at} &= \frac{\beta^2_{at}\sigma^2_{Wt} + \gamma^2_{at}\sigma^2_{Lat}}{\beta^2_{at}\sigma^2_{Wt} + \gamma^2_{at}\sigma^2_{Lat} + \sigma^2_{\varepsilon at}} \\ &= 1 - \frac{\sigma^2_{\varepsilon at}}{\sigma^2_{at}} \text{ for all } i, j \in a \end{aligned} \tag{7}$$

where σ^2_{at} is the total variance of each country belonging to region a. In the empirical section we interpret the correlation measure ρ_{at} as the 'average' or 'general' level of correlations between all countries of region a rather than the bivariate correlation between two country returns.[5] Expression (7) shows that the cross-country correlation equals the ratio of systematic to total variance, or equivalently, one minus the ratio of idiosyncratic to total variance, which resembles R^2.

Solnik and Roulet (2000) derive an expression for correlations similar to (7), under the stronger assumptions of a one-factor model with unit betas for all assets. They examine correlations by considering idiosyncratic variance only. Expression (7) shows that, ceteris paribus, correlations and idiosyncratic volatility are inversely related. However, inferences about changes in correlations solely on the basis of observed changes in idiosyncratic volatility can be misleading unless the systematic component of returns volatility remains unchanged. Indeed, the literature provides ample evidence that both market volatility and market betas are time-varying (see, for instance, Bekaert and Harvey, 1997, Ng, 2000, Campbell, Lettau, Malkiel and Xu, 2001, Baele, 2005) and this should be taken into account when making inferences about changes in correlations from changes

[5] Note that expressing the correlation as one minus the ratio of idiosyncratic volatility to total volatility, as in the second line of equation (7), can be done for any multifactor model, provided the two assets have identical exposures to all factors.

in idiosyncratic volatility. Moreover, in order to examine time-varying market integration in this setup, one should allow for both a global and a local or regional factor with time-varying factor exposures.

2.2 Estimation

We first show that although idiosyncratic volatility can be consistently estimated using cross-sectional dispersion, we need a time series dimension in order to estimate total variance. Next, we propose a novel estimator for time-varying average correlation that is robust for time-varying factor volatility and factor exposure. We also discuss the adjustment required to deal with the serial correlation induced by nonsynchronous trading. In the last sub-section, we use our theoretical setup to derive a nonparametric measure of time-varying market integration.

2.2.1 A pure cross-sectional estimator?

An important contribution of Solnik and Roulet (2000) lies in recognizing that, under the assumptions of the model, the cross-sectional dispersion of returns is a 'good' estimator of idiosyncratic volatility. Traditionally, correlations and volatility are estimated using time series methods and require long time series to provide statistically reliable estimates. The cross-sectional method, by contrast, is dynamic. By using short horizon returns it provides instantaneous information about the level of idiosyncratic volatility.

In accordance with Solnik and Roulet (2000), in our setup idiosyncratic volatility (i.e., country residual risk) can be consistently estimated using the cross-sectional dispersion of returns. Consider N countries of region a whose returns satisfy the factor process specified in equation (5). The return on an equally weighted portfolio of region a is

$$\tilde{r}_{EWat} = \beta_{at}\tilde{W}_t + \gamma_{at}\tilde{L}_{at} + \frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it}. \tag{8}$$

Given the assumption that the expected idiosyncratic return equals zero, the average idiosyncratic return within a region is likely to be close to zero. This implies that the idiosyncratic country risk is, at least to a large extent, diversified away in the regional portfolio. The difference between the returns of country i and the contemporaneous equally weighted regional portfolio equals the country's idiosyncratic return $\tilde{\varepsilon}_{it}$ minus the average idiosyncratic return. We compute the cross-sectional dispersion of returns as follows

$$v_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\tilde{r}_{it} - \tilde{r}_{EWat})^2} \tag{9}$$

$$
\begin{aligned}
&= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\tilde{\varepsilon}_{it} - \frac{1}{N}\sum_{j=1}^{N}\tilde{\varepsilon}_{jt}\right)} \\
&= \sqrt{\frac{N-1}{N}}\hat{\sigma}_{\varepsilon at}.
\end{aligned}
$$

This provides a consistent estimator of the idiosyncratic volatility based only on cross-sectional data.

In order to estimate instantaneous total variance of any country within region a, σ_{at}^2, one could suggest taking the cross-sectional sum of squared excess returns of all countries within region a: $\frac{1}{N}\sum_{i=1}^{N}\tilde{r}_{it}^2$. However, this estimator is not consistent as it converges to a random variable.[6] Intuitively, each cross-section of returns yields only one 'observation' of the common global and regional factors. Hence a single cross-section does not allow us to consistently estimate the factors' instantaneous variances or the assets total variances. This illustrates that in the presence of time variation in factor exposure and factor volatility, the econometrician needs a time dimension when estimating time-varying correlations. Indeed we cannot consistently estimate the correlation coefficient as the R^2 of a cross-sectional regression, even though expression (7) resembles an R^2. This is precisely because a cross-sectional regression will not provide us with a consistent estimate of the total variance of asset returns.

In sum, if both factor exposures and factor variances are constant (as is assumed in Solnik and Roulet, 2000) one can infer changes in correlation from changes in cross-sectional dispersion. However, to extract an explicit estimate of correlation, or to make inferences about the time variation in average correlations if either factor volatility or factor exposure or both are time-varying, cross-sectional dispersion alone is not sufficient and we need to consider time series data as well. Moreover, the pure cross-sectional approach requires a sufficient number of assets in the cross-section to obtain reliable estimates. In contrast, as highlighted below, our approach reduces the need of large cross-sections of assets. We combine time series and cross-sectional methods to per-

[6] As our observations $\tilde{r}_{it}^2$ are not independent we cannot directly apply the law of large numbers, but we must first use the specified model (5). The probability limit of the cross-sectional sum of squares is as follows:

$$
\begin{aligned}
p\lim\frac{1}{N}\sum_{i=1}^{N}\tilde{r}_{it}^2 &= p\lim(\beta_{at}^2\tilde{W}_t^2 + \gamma_{at}^2\tilde{L}_{at}^2 + \frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it}^2 + 2\beta_{at}\tilde{W}_t\gamma_{at}\tilde{L}_{at} + .. \\
&\quad ..2\beta_{at}\tilde{W}_t\frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it} + 2\gamma_{at}\tilde{L}_{at}\frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it}) \\
&= \beta_{at}^2\tilde{W}_t^2 + \gamma_{at}^2\tilde{L}_{at}^2 + \sigma_{\varepsilon at}^2 + 2\beta_{at}\tilde{W}_t\gamma_{at}\tilde{L}_{at} \\
&\neq \beta_{at}^2\sigma_{Wt}^2 + \gamma_{at}^2\sigma_{Lat}^2 + \sigma_{\varepsilon at}^2 \ (= \sigma_{at}^2).
\end{aligned}
$$

form reliable estimation of average correlations for small groups of assets over very short horizons.

2.2.2 Combining short time series and cross-sectional data

A natural candidate to provide a consistent nonparametric estimate of the total variance of each asset is the realized variance or quadratic variation of realized returns over a discrete interval (see, for instance, Merton, 1980, French, Schwert and Stambaugh, 1987, Andersen, Bollerslev, Diebold and Ebens, 2001). The quadratic variation is the sum of squared price changes over the specific horizon. In particular, let D_t be the number of trading days during month t (this is the month from time $t-1$ to time t). Then the monthly quadratic variation of country i's returns is a consistent estimate of its monthly variance and is computed from daily returns as

$$V_{it}^2 = \sum_{d=1}^{D_t} r_{id}^2, \tag{10}$$

where d denotes the day of the month. Assume that daily returns are serially uncorrelated (we relax this assumption later on) and that factor exposures and volatilities are constant within each month. One could argue that these can be time-varying on a daily basis. However, we are not able to consistently estimate daily factor variance based on daily data only, because we always need a time dimension.[7] Nevertheless, by allowing factor variances and factor exposures to vary at a monthly frequency, our approach is considerably less restrictive than assuming constant variances and betas over longer horizons. By assumption, daily returns for a specific asset in a given month are i.i.d., which implies that we can now invoke the law of large numbers. Indeed, our estimate V_{it}^2 is a consistent estimator for σ_{at}^2. By computing the non-central moment the total variance estimate is guaranteed to exceed the idiosyncratic variance estimate. According to Merton (1980) the resulting bias can be neglected for return intervals of one month or less. In addition, estimating monthly expected returns using daily data is a very difficult task and estimating variances and covariances using daily returns can be done much more accurately. Under our model's assumptions, all countries within a given region are assumed to have identical return variances. However, rather than taking the estimated variance for one single country, we compute the cross-sectional average over all countries:

$$V_{at}^2 = \frac{1}{N} \sum_{i=1}^{N} V_{it}^2. \tag{11}$$

If region a consists of N countries, we use $N \times D_t$ observations to estimate V_{at}^2. As we increase the cross-section, we can reduce the number of returns observations of each country's returns without

[7] Andersen et al. (2001) estimated daily correlations based on realized covariances and variances calculated with high frequency data. However, as we are interested in cross-market linkages, and in particular those involving emerging markets, high frequency data is typically unavailable.

affecting our volatility estimate noticeably. Moreover, each country's variance is estimated with error. If the errors for different countries are less than perfectly correlated, averaging over the cross-section removes some of the estimation error and may result in a more precise estimate of the country variance, which is assumed to be the same for each country in a certain region. We use one month of daily data for each country in the cross-section to obtain total variance estimates. Even though we also estimate idiosyncratic variance separately (based on cross-sectional dispersion), we want to estimate total variance rather than systematic variance only, as this allows us to estimate correlations without having to specify the world and regional factors nor having to estimate factor variances and exposures.

Campbell, Lettau, Malkiel and Xu (2001) also estimate monthly variances based on daily return data for a given cross-section. However, their approach is somewhat different. They assume that individual asset returns follow a two-factor model and that they can be decomposed into the market return, an industry component and a firm-specific idiosyncratic component. They adopt a market-adjusted model in order to avoid estimating betas. However, as a consequence the three return components are not orthogonal. By taking a cross-sectional weighted average the covariance terms drop out in the variance decomposition. In contrast, our two-factor model does allow for time-varying factor exposures. We avoid the need to estimate factor exposures explicitly by expressing our correlation measure as a function of assets' total and idiosyncratic variances. Our motivation for using the cross-sectional dimension stems from the fact that cross-sectional dispersion is a consistent estimator for idiosyncratic volatility. Last, we include the time dimension because it is necessary to consistently estimate the systematic component of total variances.

A similar argument for adding the time dimension to the cross-sectional dimension can be made to improve the estimation of the returns' idiosyncratic variance. We can use daily or weekly data to estimate monthly cross-sectional dispersion. Under the assumption that idiosyncratic shocks are serially uncorrelated (below we discuss how to adjust for serial correlation) and that idiosyncratic variances are constant within each month, the monthly cross-sectional dispersion for region a can be computed as

$$v_{at} = \sqrt{\sum_{d=1}^{D_t} \left[\frac{1}{N} \sum_{i=1}^{N} (\tilde{r}_{id} - \tilde{r}_{EWad})^2 \right]}. \tag{12}$$

When the cross-section of countries is large we can estimate monthly dispersion directly from the cross-section of monthly returns. When the cross-section is small, we may improve the estimation accuracy of dispersion by using the average of the daily cross-sectional dispersion over the month as our estimate. Indeed, this measure converges at a higher rate ($\sqrt{N \cdot D_t}$) than the pure cross-sectional measure.

In sum, we propose the following estimator for the instantaneous average level of cross-country correlations within region a:

$$\begin{aligned} \hat{\rho}_{at} &= 1 - \frac{v_{at}^2}{V_{at}^2}, \qquad (13) \\ \text{where } v_{at}^2 &= \frac{1}{N} \sum_{i=1}^{N} \sum_{d=1}^{D_t} (r_{id} - r_{EWad})^2 \\ \text{and } V_{at}^2 &= \frac{1}{N} \sum_{i=1}^{N} \sum_{d=1}^{D_t} r_{id}^2. \end{aligned}$$

This correlation measure is nonparametric and easy to compute, even for very large cross-sections of countries. It is robust for monthly time variation in exposures to local and global factors and factor variances. Nevertheless, we do not need to specify the factors. Using daily returns for the countries within a region, we can obtain monthly estimates of the average level of correlation between national equity returns of that region. This approach of estimating average within-group correlation is valid for returns generating processes with any number of factors. The only restrictions are that within the group for which average correlations are computed, all returns are subject to the same factors, and that over the estimation interval (i.e., a week, a month), factor volatilities and factor exposures as well as idiosyncractic volatilities are constant and identical for all assets.

As we are interested in high frequency changes in returns comovements between countries, we use daily returns from different national stock markets to estimate average correlations. When there is little or no overlap in trading hours across the markets under investigation, nonsynchronous returns have a confounding effect on the measure of comovement (see Martens and Poon, 2001, and Sander and Kleimeier, 2003). Further, nonsynchronous and infrequent trading induce serial correlation in daily returns. So far, our estimators assume zero serial correlation. To adjust for first-order serial correlation, we use the Newey West (1987) approach. This adjustment guarantees positive variance estimates. The monthly variance for individual assets is calculated as[8]

$$V_{it}^2 = \sum_{d=1}^{D_t} r_{id}^2 + \sum_{d=2}^{D_t} r_{id} r_{id-1}. \qquad (14)$$

Similarly, for monthly dispersion we have

$$\begin{aligned} v_{at}^2 &= \frac{1}{N} \sum_{i=1}^{N} v_{it}^2 \\ \text{where } v_{it}^2 &= \sum_{d=1}^{D_t} (r_{id} - r_{EWad})^2 + \sum_{d=2}^{D_t} (r_{id} - r_{EWad})(r_{id-1} - r_{EWad-1}). \qquad (15) \end{aligned}$$

[8]The adjustment term for first order serial correlation is $\frac{1}{D_t} \sum_{d=2}^{D_t} r_{id} r_{id-1}$. This term needs to be added twice. Then, the Newey West weight is $w(k,q) = 1 - \frac{k}{q+1} = 0.5$ where $k = q = 1$, i.e. the total number of lags. Finally, we multiply the term by D_t to convert it to a monthly frequency.

2.3 Measuring time-varying market integration

In this section we extend our approach to derive a nonparametric measure of time-varying market integration. Our interest is to determine the extent to which comovements in asset returns change over time as a result of integration of the goods or the financial markets. Financial market integration is characterized by the existence of a unique pricing kernel pricing all assets in the economy (e.g. Solnik, 1974, Sercu, 1980, Adler and Dumas, 1983) while segmentation is characterized by country or region specific pricing kernels (e.g. Stulz, 1981, Errunza and Losq, 1985, Bekaert and Harvey, 1995 - for a survey see Stulz, 1995). The process of financial integration will therefore affect the expected returns of the assets and increase the commonality of expected returns. However, for short horizon returns (daily, weekly or monthly) this is likely to have a very small effect on the commonality of equity returns since for equities, expected returns are small in comparison to returns innovations. Integration of the real economy will however likely induce increased exposure to the common factors which will drive the commonality in returns innovations.[9] For highly integrated markets, the systematic risk is dominated by global factors, whereas local factors play a much more important role for more segmented markets.

Cross-country correlations convey information on the comovements between national equity markets. One could expect higher correlations between countries that are more integrated into the world market, as those countries are subject to the same global factors. However, it can be hazardous to use correlations to make inferences about market integration. Correlations might increase simply because of increasing common factor variance, rather than increasing market linkages, as can be seen from equation (7). This is an example of the interdependence problem discussed by Forbes and Rigobon (2002). Moreover, as Dumas, Harvey and Ruiz (2003) point out, in order to use equity return correlations for statements of market integration, one should control for the correlations in economic fundamentals. A similar argument is made by Carrieri, Errunza and Hogan (2005) who find that correlations typically underestimate the level of market integration.

The literature provides several measures of time-varying market integration. For instance, Bekaert and Harvey (1995) model market integration parametrically, using a regime switching model. They measure integration as the conditional probability of being in the full integration state. Bekaert and Harvey (1997) use a dynamic factor model and consider, amongst others, the exposure with respect to the world factor and the correlation between the country returns and the global factor to make inferences on market integration. On the other hand, De Jong and De Roon

[9] These are exactly the results that Aydemir (2004) obtains in a general equilibrium model which formalizes the intuition, and provides a rigorous comparison of the impact of integration of financial markets and integration in the goods market on cross-country equity correlations (see also Dumas, Harvey and Ruiz (2003) for a quantification of the magnitudes of the change in correlations that could be due to financial integration alone).

(2005) use the ratio of the market value of non-investable assets to the total market value of all assets as an indicator of the level of integration. Carrieri *et al.* (2005) propose the integration index, which is based on the fraction of the variance of non-investable assets that is not spanned by the investable assets. These integration measures are typically based on parametric models, on macro-economic data or on more detailed information on investable and non-investable assets.

Our two-factor model decomposes total country variance into global, regional and country residual risk. We can use this setup to derive a measure of market integration, which can be estimated nonparametrically using national equity returns data only. Similar to Bekaert and Harvey (1997) we measure integration as the fraction of total risk due to global factors. Hence, the level of integration of the countries of region a into the world market at time t is expressed as follows:

$$I_{at} = \frac{\beta_{at}^2 \sigma_{Wt}^2}{\beta_{at}^2 \sigma_{Wt}^2 + \gamma_{at}^2 \sigma_{Lat}^2 + \sigma_{\varepsilon at}^2}. \tag{16}$$

This measure is bounded between zero and one and has a straightforward interpretation. If a market is segmented from the world market, local factors will dominate and the integration measure will be close to zero. On the other hand, a more integrated market is subject mainly to global risks and has an integration measure that is close to one.[10]

In our setup, cross-country correlations within region a can be expressed as the ratio of global and regional risk over total risk. Hence, cross-country correlations are related to the average degree of integration of those countries within the world market as follows:

$$\rho_{at} = I_{at} + \frac{\gamma_{at}^2 \sigma_{Lat}^2}{\sigma_{at}^2}. \tag{17}$$

This expression shows that average cross-country correlations within region a equal the integration of those countries within the world market plus the fraction of total variance due to the regional factor (orthogonal to the world factor). This variance ratio can be interpreted as a measure for regional segmentation, as an increase implies that the regional factor explains a larger fraction of total variance of the country returns in region a, i.e., ceteris paribus, the region becomes more segmented from the world market. Expression (17) can be interpreted as follows. As countries are becoming more integrated within the world market, their returns are being more affected by the same global factor. This increases the commonality in returns and has a positive effect on cross-country correlations. Additionally, as the region is becoming more segmented from the world

[10] Although we do not consider expected returns when measuring integration, expected returns can be affected by changing levels of integration. For instance, when the exposure to the global factor increases, the integration measure increases and at the same time, the expected returns ($\beta_{at}\mu_{Wt}$) are affected. Note that these parameters are all allowed to vary at a (two-) monthly frequency.

market and regional factors are becoming more important, the commonality in country returns from that region also increases and cross-country correlations also increase.

In order to take a closer look at the relative importance of global versus regional factors, we also consider the following variance ratio:

$$\text{Global / systematic risk: } \frac{\beta_{at}^2 \sigma_{Wt}^2}{\beta_{at}^2 \sigma_{Wt}^2 + \gamma_{at}^2 \sigma_{Lat}^2}. \tag{18}$$

This variance ratio is similar to our integration measure, but excludes the country residual risk. It provides information about the contribution of global and regional factors to a country's systematic risk. An argument could also be made that when country residual risk can be diversified away, the fraction of systematic risk due to global factors is a more appropriate measure for market integration than the fraction of total risk due to global factors. In the equally weighted regional index (eq. (8)) the country idiosyncratic risk is indeed largely diversified away. While it is relatively easy in developed market regions to invest in the regional index with little or no country risk, in emerging markets the regional index might not be fully investable due to possible capital market barriers. In this case, country residual risk is relevant when assessing the level of market integration. Hence, whereas we measure integration as the fraction of total variance due to global factors, for developed markets the global / systematic risk ratio might be used as an alternative measure of integration. Indeed, Bekaert, Hodrick and Zhang (2005) use this variance ratio to examine integration of developed markets into the world market. However, in emerging markets country residual risk may still play an important role and the global / systematic risk ratio can simply be used to examine the relative importance of global and regional factors.

We can estimate the integration measure I_{at} and the ratio of global over systematic risk based on our two-factor model, using a similar nonparametric approach as for the correlation measure. Whereas we do not need to specify the local and global factors to estimate our correlation measure, in order to estimate these two variance ratios we do need to specify the factors. First, we use the value-weighted world index as the global factor. We estimate its variance in a similar fashion as the variance of individual country returns, as the sum of squared daily excess returns adjusted for first order serial correlation (similar to equation (14)). As the regional factor, we use the regional index return that is orthogonalized to the world factor. We proceed as follows.

First, remember that we can write the return on the equally weighted index of region a as follows:

$$\tilde{r}_{EWat} = \beta_{at}\tilde{W}_t + \gamma_{at}\tilde{L}_{at} + \frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it},$$

where the regional factor $\tilde{L}_{at}$ and the idiosyncratic returns $\tilde{\varepsilon}_{it}$ are all orthogonal to the world factor $\tilde{W}_t$. The average idiosyncratic return is likely to be very small, as country idiosyncratic risk can be diversified over all countries in the region. Hence, the difference between the return on the equally weighted regional index and the return on the world factor is orthogonal to the world factor and it is dominated by $\gamma_{at}\tilde{L}_{at}$.

We assume constant factor exposures and variances for all days within a certain month. We estimate the following regression for daily returns using Ordinary Least Squares (OLS henceforth):

$$r_{EWad} = \hat{c} + \hat{b} r_{Wd} + \upsilon_d, \tag{19}$$

where $\tilde{r}_{Wd}$ is the daily excess return on the value-weighted world index and $\hat{b}$ is the estimated exposure of the equally weighted regional index to the world index. The error term υ_d is by construction orthogonal to the world index return. Hence, the regression coefficient $\hat{b}$ is a consistent estimator for β_{at} and the residual risk of the regression is an estimate of the variance $\gamma_{at}^2\sigma_{Lat}^2$ plus $Var(\frac{1}{N}\sum_{i=1}^{N}\tilde{\varepsilon}_{it}) = \frac{1}{N}\sigma_{\varepsilon at}^2$. The latter term is likely to be very small and will be dominated by $\gamma_{at}^2\sigma_{Lat}^2$. Hence, we use $Var(\upsilon_d)$ as an estimator for $\gamma_{at}^2\sigma_{Lat}^2$.[11] Due to the specification of our integration measure and the ratio of global over systematic variance we do not need separate estimates of the regional factor variance and the exposure to the regional factor and we can therefore estimate the two in one step. Since we use OLS to estimate this regression on daily returns, we need to correct for serial correlation. Therefore we apply the Newey West (1987) adjustment to the variance estimate of the error term. In the previous section we explained how to combine short time series and cross-sectional data to estimate monthly correlations. Since for the estimation of world and local factor variance we only have a time series dimension (i.e., no cross-section), one month of daily return observations is generally too little for sufficiently reliable estimates. Therefore, for the integration measure and for the ratio of global over systematic risk we use two-month estimation periods.

While the regression coefficient $\hat{b}$ is a consistent estimate of β_{at}, we can use our two-factor model to derive an alternative estimator for the factor exposure. The advantage of the latter is that it is based on both a time series and cross-sectional dimension and hence, it uses more information. Using our estimates of total, global, regional and country residual variance, we can extract an estimate of β_{at} from our variance decomposition in equation (6) as follows:[12]

$$\hat{\beta}_{at} = \sqrt{\frac{\hat{\sigma}_{at}^2 - \hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2 - \hat{\sigma}_{\varepsilon at}^2}{\hat{\sigma}_{Wt}^2}}. \tag{20}$$

[11] The same result can be found when assuming that $\sum_{i=1}^{N}\tilde{\varepsilon}_{it} = 0$.

[12] According to equation (20) we only allow for positive betas. It is reasonable to expect positive exposures of country returns to a world factor. Nevertheless, our general setup also allows for negative factor exposures $\hat{\beta}_{at} = -\sqrt{\frac{\hat{\sigma}_{at}^2 - \hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2 - \hat{\sigma}_{\varepsilon at}^2}{\hat{\sigma}_{Wt}^2}}$, but we do not consider this solution for $\hat{\beta}_{at}$.

Our approach guarantees that $\hat{\sigma}_{at}^2 - \hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2 - \hat{\sigma}_{\varepsilon at}^2 \geq 0$ because we use the return on the equally weighted regional index as a dependent variable in regression (19). To see this, first note that the difference between the total and idiosyncratic variance estimates equals the estimated variance of the equally weighted regional index. The regional risk $\hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2$ is estimated as the variance of the error term of regression (19). As the return on the equally weighted regional index is the dependent variable of this regression, by construction its variance exceeds the variance of the error term. Hence,

$$\hat{\sigma}_{at}^2 - \hat{\sigma}_{\varepsilon at}^2 = Var(\tilde{r}_{EWat}) \geq \hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2$$

and therefore the condition that $\hat{\sigma}_{at}^2 - \hat{\gamma}_{at}^2\hat{\sigma}_{Lat}^2 - \hat{\sigma}_{\varepsilon at}^2 \geq 0$ is met.[13]

Now we have all necessary estimates to calculate the integration measure following expression (16). Similarly, we can construct an estimate for the fraction of systematic variance due to global factors. Our measure of time-varying integration has a number of important advantages. First, it allows for time variation in global and local factor variances. The exposures to these factors are allowed to vary over time as well. Second, this measure is nonparametric and can be estimated easily for a large number of countries. Third, it is based purely on daily return data. Last, the measure has a straightforward interpretation, since it is bounded between zero and one. As it is a continuous measure, we allow for different levels of partial segmentation. Note that measuring integration as the fraction of total risk due to global factors is not a novel idea (for instance, Bekaert and Harvey (1997) use a similar integration measure). Our contribution is the nonparametric approach to estimating the country, regional and global variances and factor exposures, based on the two factor model, using short time series and cross-sectional data.

3 Data

Our empirical investigation focuses on the variation over time in the average comovements across a large cross-section of national equity markets. Specifically, we are interested in the worldwide level of stock market linkages and the changes in comovements between developed markets and between emerging markets. Our dataset consists of national market indices of 50 countries, which we subdivide into seven regions. The sample includes 24 developed markets from North America (2), Europe (17) and Asia Pacific (5) for which we use Datastream indices. The data for the 26 emerging markets is based on Datastream indices up to July 1995, thereafter we use data from Standard and Poor's Emerging Markets Data Base. These includes markets from Eastern Europe

[13] When performing the calculations we find that this condition is not met in a few instances due to the Newey West adjustment in the variance estimators. In this case we replace the resulting imaginary beta by zero. Without the Newey West adjustment the condition is met by construction.

(6), the Middle East and Africa (5), Asia (8) and Latin America (7). In Table.1 the countries are ordered according to this classification. Our full sample period extends from January 1973 to February 2005. However, not all countries are available for all 32 years. We consider a region as soon as data is available for at least two countries. The remaining countries are included when their indices become available. As a result, different regions have different sample lengths. Whereas the sample periods for the three developed market regions all start in January 1973, the four emerging market regions start later. Eastern European country returns data is available from December 1991, data for the Middle East/Africa start in February 1993, while for the Asian and Latin-American emerging markets, the samples start in February 1987 and August 1989 respectively. Hence, the sample periods for the different regions include 12 up to 32 years.

For the developed market regions we compute daily returns from January 3, 1973 to February 28, 2005 based on total return indices with dividends reinvested. In total we have 8389 daily return observations, from which we construct 386 monthly correlation and variance estimates from January 1973 to February 2005. We estimate integration for 193 two-month periods. For the emerging market regions we use the same approach for the appropriate sample periods.[14] We take the perspective of a US investor, hence all total return indices are denoted in USD and the returns are net of the US daily risk free rate. The daily risk free rate is the 30-day T-Bill rate, downloaded from Kenneth French's website, divided by the number of trading days within the month.

Our variance estimators V_{at}^2 and v_{at}^2 for total and country residual risk are adjusted for serial correlation that may arise due to nonsynchronous trading. We also adjust returns for non-common holidays (days on which all stock markets are closed are excluded from our sample automatically).[15]

Table.1 reports summary statistics of the daily excess returns of the 50 countries and the G50 value-weighted market index. The mean and standard deviation are annualized assuming a 260-day year. Mean excess returns on emerging markets national indices are on average higher than

[14] This results in 135 monthly correlation estimates for Eastern Europe, 145 for the Middle East / Africa, 217 for the emerging markets in Asia and 187 for Latin America.

[15] We proceed as follows. Suppose that the US market is closed on day d. Then the US return of day $d+1$ is actually a two-day return. We divide the return of day $d+1$ by two and replace the returns of both days by this average return. For two subsequent holidays, the zero returns are replaced by one third of the return of the third day. As it is highly unlikely that no trade would occur on a day a developed market is open, we treat all zero return days in developed markets as holidays. In emerging markets trading is not as deep and a zero return may be recorded simply because of infrequent trading. It would then be inappropriate to adjust for it. As we do not have data on the exact holidays in all emerging markets, we treat zero return days in these markets as follows. Two or more subsequent zero return days are treated as holidays (assuming that it is unlikely that on two subsequent days no trades were made while the market was open) and days when more than half of the emerging markets have zero returns are considered as holidays as well. After these adjustments, only a small fraction of daily observations remains zero returns.

developed markets mean returns, but they are also more volatile. The annualized excess US return over the last 32 years is 5.9 percent and its volatility is 15.9 percent. Brazil, one of our 'emerging' markets, has an average excess return of 14.8 percent per annum and an annual volatility of 36.3 percent over the last 11 years. From 1973 to 2005, the global G50 value-weighted market index has an average excess return of 4.9 percent with an annual standard deviation of 11.9 percent. Table.1 also provides the market value weights of the countries in the G50 market index at the beginning and at the end of the sample period. Among developed markets, the US has shown the largest decrease, its weight in the G50 index falling from 65.9 percent in 1973 to 43.1 percent in 2005. This is to some extent affected by the inclusion of more countries in the G50 index as time evolves. All emerging markets have average weights of less than 1 percent in the global index. Some have gained in importance, for example China's weight increased from 0.01 to 0.60 percent. Others have a lower weight in 2005 than in the beginning of their sample period, like Argentina (whose weight decreased from 0.27 percent to 0.03 percent).

4 Correlation and integration estimates

We estimate the overall level of correlation and its components for the set of 50 countries subdivided into seven regions. Recall that for our correlations estimates we do not need to specify the global and regional factors. All we need are estimates of the total variance V_{at}^2 and country residual variance v_{at}^2 for each region a. In order to estimate the integration of each region into the world market, we specify the value-weighted G50 world index as the world factor. The regional factor is obtained by orthogonalizing the return on the equally weighted regional index to the world index return.[16] We use daily excess returns to construct monthly correlation estimates. As we only have a time dimension and no cross-sectional dimension to estimate factor variances, we use two-month estimation periods for the integration measure and the ratio of global over systematic variance. We treat the resulting time series as observable, similar to e.g. Campbell *et al.* (2001) and Ferreira and Gama (2005).[17]

Figure.1 reports the correlation time series estimates as well as the 12-month moving averages.

[16] As we construct the world and regional indices using all countries that are available during a certain month, they may be affected by the inclusion of more countries over time. Hence, we also perform the analysis for the period from 1995 to 2005 when all countries are available. We find that the results are generally robust. However, due to the smaller number of observations, the significance level of the time trends is lower.

[17] Note that we investigate cross-country correlations and market integration for each of the seven regions separately. We do not consider all 50 countries as one group, since this would require the overly stringent assumption of fully integrated markets. This follows from our model according to which all countries under consideration are subject to the same risk factors. By investigating the regions separately we allow for different regional factors.

Clearly there is substantial time variation in the correlation between national equity markets. For the developed European markets and for Asia Pacific average cross-country correlations seem to trend upward. North America has the highest correlation estimates, which are often close to 0.9. Correlations between Middle Eastern and African countries appear to decrease, while for Eastern Europe, emerging Asian markets for and Latin America the pattern is less clear, although that may be due to shorter sample periods.

Figure.2 shows the decomposition of total variance for the countries within each region into global risk (the dark grey area), regional risk that is orthogonal to the global factor (the white area) and country residual risk (the light grey area). For ease of exposition, the figures are based on 12-month moving averages. The dark grey area corresponds to the integration measure (i.e., the fraction of total risk due to global factors). Cross-country correlations are measured as the fraction of total risk that is systematic global and regional risk. Hence, the dark grey and white areas combined correspond to our correlation measure.

First of all, the figure shows that the estimated levels of market integration are highly time-varying. The integration measure of the developed European markets displays a remarkable increase over time. Whereas in 1973 about eight percent of total variance is due to global factors, in 2005 this has risen to over 40 percent. The regional risk is relatively stable and the country residual risk decreases over time. The variance decomposition of Asia Pacific shows a similar pattern. Integration increases from eight percent in 1973 to about 30 percent in 2005. Also, the fraction of risk due to regional factors seems quite stable, while country risk decreases. The increase in global risk and decrease in country-specific risk has lead to an increase in cross-country correlations and integration measures in both of these regions.

North America appears to be highly integrated in the first and last decades of the sample period, when its integration measure is about 0.7. On the other hand, between 1985 and 1995 the measure is strikingly lower, dropping to levels close to 0.2 in the mid nineties. This suggests that during these 10 years the US and Canada have been more segmented from the world market. This is probably related to the increasing weight of Japan in the G50 index in the period preceding the Asian crisis in 1997. Indeed, Table.1 shows that the weight of Japan was about 15 percent in 1973 and 11 percent in 2005. However, the average weight over the full sample period is about 24 percent. Moreover, whereas in the beginning of our sample period the value-weighted world index consists mainly of the US, during the next 20 years more countries are added. We use this index as the global factor, which may explain why North America's integration measure is decreasing during this period.[18] Indeed, the figure shows that the risk due to the regional factor (which has

[18] As a robustness check we also use the equally weighted G50 index as a proxy for the global factor. However, unreported results show that now North America appears to be one of the least integrated regions, which seems

been orthogonalized to the world factor) increases during this period. The country residual risk within this region is relatively stable over time.

The integration measures of the four emerging market regions are all at a lower level, indicating that, as would be expected, these markets are generally less integrated into the world market. Furthermore, there is no obvious trend visible in the figures. The main share of total risk is country residual risk and regional risk seems to be slightly decreasing over time, especially for countries in the Middle East and Africa and in Latin America.

Table.2 reports summary statistics of the estimated time series of correlation and integration measures and the ratio of global over systematic variance. On average, the North American countries are most highly correlated (the mean correlation between Canada and the US over the last 32 years is 0.80) and the countries in the subgroup Middle East/Africa are least correlated (0.29 for the last 12 years). The developed markets are on average more correlated than the emerging markets. Unreported results show that over the 1994 to 2005 period during which all regions are available, the average cross-country correlation between developed markets is 0.58, while for emerging markets it is only 0.31. According to our integration measure, over the full sample period, North America is most integrated in the world market (on average 52 percent of the total variance is due to the world factor) and the Middle Eastern - African region is the least integrated (the average integration measure is only 6.6 percent). The ranking of the regions based on the fraction of systematic risk due to global factors is similar to the ranking based on the integration measure. In particular, this variance ratio is highest for North America (on average 64 percent of the systematic variance is due to global factors) and it is lowest for the Middle Eastern - African region, where on average 23 percent of the systematic variance is due to the global factor and 77 percent is due to the regional factor.

Indeed, although insightful, these figures and the summary statistics give us only limited information about the evolution of global market comovements over time. Hence, in the next sections we employ more sophisticated methods to further analyze these time series.

5 Trends in correlation and integration

In this section we examine whether the estimated time series of correlation and integration measures and of the fraction of global over systematic variance exhibit stochastic or deterministic trends. First we study their autocorrelation structure, which is reported in Table.3 for 1 up to 12 lags.

very unrealistic. In future robustness checks we plan to use the value-weighted G49 index, excluding the US, as an alternative global factor. Also, we could use a fixed weight of the US in the G50 index. For instance, we could set the US weight in all months equal to the average weight over the full sample period.

Indeed, as would be expected, the three series are substantially autocorrelated for the set of seven regions. Whereas the measures typically exhibit positive autocorrelation, the integration measure of the Middle East/Africa region and the ratio of global over systematic risk of this region and of the emerging markets in Asia show small negative serial correlation for a number of lags. The level of persistence suggests that the correlation and integration series can be predicted to some extent by their past values. We continue the analysis by examining the presence of stochastic trends.

In order to test for a unit root, we perform the augmented Dickey Fuller (ADF) test with intercept and with intercept and time trend using one lag. Table.4 reports the results and shows that for all three series we can reject the null hypothesis of a unit root, for all seven regions. This means that the time series of correlation, integration and the ratio of global over systematic risk are stationary and shocks only have a temporary impact.

5.1 Deterministic trends

Next we test for a deterministic linear time trend. A simple procedure is to perform an OLS regression with a time trend as independent variable. If the error terms are stationary, OLS estimates are efficient. If the errors have a unit root, optimality can be achieved by taking first differences. However, often it is unknown whether the errors are I(0) or I(1) and when there is substantial serial correlation, neither I(0) nor I(1) asymptotics are appropriate (Vogelsang, 1998). As there is substantial serial correlation in our data, we cannot use the simple OLS procedure to test for a deterministic trend. Instead, following Campbell *et al.* (2001) we use the Vogelsang (1998) procedure. The advantage of this method is that estimates of serial correlation parameters are not needed and it is robust for both I(0) and I(1) errors. Furthermore, it is asymptotically invariant to all serial correlation parameters. The test is based on the following two regressions, both estimated by using OLS:

$$y_t = \mu + \beta t + u_t \tag{21}$$

$$z_t = \mu t + \beta SDT_t + S_t, \tag{22}$$

where

$$z_t = \sum_{j=1}^{t} y_j,\ SDT_t = \sum_{j=1}^{t} t_j \text{ and } S_t = \sum_{j=1}^{t} u_j. \tag{23}$$

The z_t regression (22) is obtained by computing partial sums the y_t regression (21). The statistics for the significance of β and μ are simple modifications of standard t-statistics computed by OLS. Let t_z denote the t-statistics for testing the null hypothesis that the individual parameters in the z_t regression are zero. We adjust it as follows:

$$t - PS^1 = T^{-1/2} t_z \exp(-bJ_T^1) \tag{24}$$

where b is a constant. In order to compute J_T^1 we perform the following OLS regression

$$y_t = \mu + \beta t + \sum_{i=2}^{9} c_i t^i + u_t. \tag{25}$$

Then J_T^1 can be calculated as

$$J_T^1 = (RSS_Y - RSS_J)/RSS_J, \tag{26}$$

where RSS_Y is the residual sum of squares from eq. (21) and RSS_J is the residual sum of squares from eq. (25). When $b > 0$ the J_T^1 statistic is used to smooth discontinuities in the limiting distributions of the statistics as the errors go from I(0) to I(1). Given a significance level of the test, b can be chosen such that the critical values of the $t - PS^1$ statistic are the same when u_t is I(0) and when it is I(1). Therefore, J_T^1 makes sure that the t-tests from the z_t regressions are robust for I(1) errors. The critical values of these test statistics and the optimal values of constant b can be found in table II(i) of Vogelsang (1998). We use two-sided tests with a 95 percent significance level. Thus, we use $b = 0.716$ and the critical value is ± 1.720.

First, we test for deterministic trends in average cross-country correlation series for each of the seven regions. The results are reported in Table.5. We detect significant positive trends in correlations for two developed market regions only. For the developed European markets cross-country correlations have increased significantly by 0.63 percent per annum over the last 32 years.[19] During this same period correlations between developed Asian and Pacific countries have risen by 0.33 percent per year. Next to their statistical significance, these numbers are also economically meaningful. The substantial increase in correlations during this extensive time period implies decreasing cross-country diversification potential in these regions. The positive trend coefficient of North America lacks statistical significance. Not all regions show increasing cross-country correlations. The emerging markets in the Middle East and Africa, Asia and in Latin America have negative trend coefficients, but these are not statistically significant. The positive trends of Eastern Europe is not significant either. Note that we perform these tests for various sample lengths, depending on the data availability of each region. In order to make a better comparison across regions, we perform the tests for each region starting in January 1994, when all seven regions are available. Unreported results confirm our previous findings: cross-country correlations within the developed markets in Europe and Asia Pacific trend upwards, while for the other regions we do not detect significant time trends.

The international finance literature provides ample evidence of time-varying correlations between national stock markets. However, most papers focus on developed markets only. Koch and

[19] In table 5 it can be seen that the estimated monthly trend of this region is $52.574 \cdot 10^{-5}$. This results in an annual trend of $52.574 \cdot 10^{-5} \cdot 12 = 0.0063$.

Koch (1991) examine market comovements between eight developed markets using high frequency data. Based on three one-year periods (1972, 1980 and 1987) they conclude that the comovements increase over time. King, Sentana and Wadhwani (1994) examine cross-country correlations for 16 developed markets between 1970 and 1988. Their results indicate that the increase in correlations during their sample period was due to the 1987 crash and was transitory. They conclude that there is no time trend in cross-country correlations. Longin and Solnik (1995) examine cross-country correlations between 1960 and 1990 for seven developed markets and report an upward sloping time trend. Goetzmann, Li and Rouwenhorst (2005) consider a sample of up to 50 countries starting as early as 1850. From 1850 to approximately 1890 cross-country correlations decreased. Then, up to roughly 1930 they increased, followed by a dramatic decrease. As of the 1950s cross-country correlations seem to increase. These patterns may be affected by the inclusion of more countries over time. Using an APT model with regional and global factors, Bekaert, Hodrick and Zhang (2005) examine model-implied cross-country correlations for 23 developed markets. Similar to our findings, they report a significant upward trend in correlations between developed European markets, while they do not detect time trends in correlations for North America either. However, whereas we detect a clear upward trend for the developed Asian markets, they do not find any evidence for time trends in this region. Finally, Solnik and Roulet (2000) find a downward trend in cross-sectional dispersion between 1971 and 1998 for 15 developed markets, and Baur (2006) reports a downward trend for eleven developed markets between 1969 and 2002. They both infer an upward trend in cross-country correlations.

However, as we argued in a previous section, making inferences on correlations based on idiosyncratic variance (estimated by cross-sectional dispersion) is hazardous unless factor variances and exposures are stable over time. This can indeed be seen from our empirical results. To this end we investigate the behavior of the components of our correlation estimates; the total and idiosyncratic variance estimates. Unreported results show that for all regions there is indeed substantial time variation in both global and regional systematic risk. This illustrates the need for taking all elements of cross-country correlations into account. Take the developed European markets. Figure.3 presents the time series of correlation estimates as well as the time series of idiosyncratic risk estimates. The figure shows that in some periods idiosyncratic risk and correlations both increase (e.g. between 1998 and 2000) or both decrease (e.g. between 1992 and 1998), which shows that indeed they do not necessarily have an inverse relationship. Furthermore, while according to the Vogelsang (1998) test the idiosyncratic variance estimate (based on cross-sectional dispersion) does not have a significant time trend (results not included in the paper), it would be erroneous to conclude that correlation remained stable over time. Indeed, over the last 32 years correlations for these 17 European countries have increased significantly.

Naturally, a constant deterministic linear trend is inconsistent with the definition of the correlation coefficient, which is bounded between minus one and plus one. However, as Longin and Solnik (1995) point out, even though it is possible to test for or model other trend specifications, these specifications cannot be derived from economic theory. Over our sample period the correlations fall clearly within the boundaries and we find evidence for linear trends over the past 32 years. However, we cannot conclude that these trends will continue indefinitely as the correlation coefficient is bounded.

Table.5 also reports tests for deterministic trends in the estimated integration measures of the seven regions into the world market. We detect significant upward trends for the developed European markets and Asian Pacific markets. The integration measures of countries in the other regions do not display significant time trends, which confirms our inference from Figure.2. Nevertheless, we detect a remarkable increasing importance of the global factor relative to the regional factors in five out of the seven regions. Table.5 shows that the ratio of global over systematic variance displays significant upward time trends for the developed European and Asian markets, Eastern Europe, and the emerging markets in Asia and in Latin America. The most striking time trend is that of Latin America, where the fraction of systematic risk due to global factors has increased by 3.0 percent per year for this region.

The upward time trends in the relative importance of global versus regional factors could suggest that these regions are becoming more integrated into the world market. However, paradoxically, we only find upward time trends in integration for two regions. This result can be explained by country residual risk, because the only difference between the two variance ratios is that the integration measure also includes country residual variance. In Section 2.3 we argued that for the developed markets, the fraction of systematic risk due to global factors can also be interpreted as a measure of market integration. This is because for these markets, (most of the) country residual risk can be diversified away and therefore it does not necessarily need to be included in the integration measure. The results show that the conclusions based on the ratio of global over systematic variance as a measure of integration would be the same as for our integration measure: the developed markets in Europe and Asia Pacific are becoming more integrated into the world market, while the level of market integration of North America does not display any time trends.

In contrast, in emerging market regions the country residual risk many not be fully diversifiable due to capital market barriers. Therefore, when measuring the integration of emerging markets into the world market, country residual risk should be taken into account. It is exactly in these regions that the two variance rations show different results. While emerging markets' systematic returns are increasingly determined by global rather than regional factors, their country residual risk is not declining over time. This is can be seen from the lack of time trends in cross-country correlations. Correlations can be expressed as one minus the ratio of country residual risk over total risk, or equivalently, the ratio of total systematic risk over total risk. Absence of trends in cross-country correlations implies that the ratio of systematic risk to total risk remains stable over time. Nevertheless, the composition of systematic risk has changed, as it has taken a more global than regional nature.

Papers examining market integration typically focus on emerging markets. Bekaert and Harvey (1995) consider a sample of 12 emerging markets from 1975 to 1992. They find that some, but not all countries are becoming more integrated into the world market. De Jong and De Roon (2005) argue that emerging markets have become less segmented from the world market, based on a sample of 30 emerging markets from 1988 to 2000. Carrieri, Errunza and Hogan (2005) show that between 1977 and 2000 the eight emerging markets under consideration are becoming increasingly more integrated into the world market, although during some periods markets are becoming less integrated. There are some papers that examine the integration of developed markets into the world market. For instance, Carrieri, Errunza and Sarkissian (2004) find that the conditional cross-country correlations between 17 OECD countries have increased between 1976 and 2003. Also, Baele (2005) finds that there is an increasing degree of market integration for 13 Western European countries. Bekaert, Hodrick and Zhang (2005) argue that some of the 23 developed markets in their sample integration has increased from 1981 to 2003, while for other countries it has decreased or there is no clear pattern at all.

It is possible that deterministic trends were not found significant because we disregarded a structural break. In order to evaluate this possibility we use the Vogelsang (2001) method to test for shifts in deterministic trends. This methodology is similar to that discussed above and also allows for various forms of serial correlation. We test three models, allowing for a shift in the intercept, a shift in the trend and a shift in both the intercept and the trend. The y_t regressions are adjusted as follows

$$\begin{aligned}
\text{Model 1, shift in intercept} &: \quad y_t = \mu + \beta t + \delta DU_t + u_t \\
\text{Model 2, shift in trend} &: \quad y_t = \mu + \beta t + \gamma DT_t + u_t \\
\text{Model 3, shift in intercept and trend} &: \quad y_t = \mu + \beta t + \delta DU_t + \gamma DT_t + u_t,
\end{aligned}$$

where

$$\begin{aligned}
DU_t &= 1 \text{ if } t > T_b \text{ and } 0 \text{ otherwise} \\
DT_t &= t - T_b \text{ if } t > T_b \text{ and } 0 \text{ otherwise}
\end{aligned}$$

and T_b is the (estimated) break date. The z_t regressions follow by taking partial sums of the y_t regressions. The hypotheses of interest (i.e., no break) are:

$$\begin{aligned} \text{Model 1} &: \quad H_o : \delta = 0 \\ \text{Model 2} &: \quad H_o : \gamma = 0 \\ \text{Model 3} &: \quad H_o : \gamma = \delta = 0. \end{aligned}$$

The calculation of the PS^1 statistic is similar that of the $t - PS^1$ statistic discussed above, for details see Vogelsang (2001). As specific break dates for the full set and the different regions are not available, we estimate the most likely break dates. To this end, we employ the supremum statistic of Andrews (1993), by which we choose the date that results in the maximum Wald statistic of the test for a break in the y_t regression (of the model under consideration). We do not consider break dates near the end points of the sample period, therefore we use 10% trimming. Hence, the first possible break date we consider is $0.10{\cdot}T$ and the last one is $0.90{\cdot}T$. The values of the parameter b and the critical values can be found in Table 4 of Vogelsang (2001).[20] [21]

Table.6 reports the results of these tests. We find a significant break in cross-country correlations in the Middle East/Africa, according to all three models. Models 1 and 3 estimate the break date in June 1995. If we take a look at Figure.1, we indeed see that in this year the correlation estimates drop from 0.5 to about 0.3. This could be related to the inclusion of more countries in 1995. We also detect a significant shift in the trend of the correlation estimates of the emerging Asian markets in December 1988. This takes place in the beginning of the sample period, which starts in February 1987. Figure.1 shows that whereas in the first few years correlations decrease, thereafter they show a general increasing pattern. For both of these regions we were not able to detect significant time trends in correlations. Hence, the wide confidence intervals of the estimated full sample trend coefficients could be caused by the presence of these breaks. Therefore, we perform the Vogelsang (1998) test for a deterministic trend again, but now for the sample periods before and after the estimated break date separately. The results are reported in Table.7. As the estimated break date of the emerging markets in Asia is in the beginning of the sample period, we only consider the sub-sample period after the break date. For this period starting in January 1989 we do not detect a

[20] The 95% 2-sided critical values for models 1 to 3 are ± 4.205, ± 3.387 and ± 5.312 respectively.

[21] These tests only allow for the presence of one break. Consequently, if a break is detected this implies that there will be not be another break in the remainder of the series. It is hard to find economic arguments why time-varying correlations or integration measures would only exhibit one structural break. However, our motivation for testing for structural breaks is not based on economic arguments but on statistical arguments. We simply check whether the tests for deterministic trends resulted in wide confidence intervals because we ignored a break. Reasons for finding a break could, for instance, be the inclusion of more countries into the analysis when more data becomes available. This type of break does not have an economic interpretation and is purely data-driven.

significant time trend, which reinforces the previously reported results. For the Middle East/Africa we do find significant a negative time trend after the estimated break date. The estimated trend before the break date also has a negative coefficient, albeit insignificant. This suggests that we were not able to detect the decreasing trend in cross-country correlations within this region due to the presence of a structural break. Indeed, over the last decade Middle Eastern and African countries have become significantly less correlated at a rate of -0.50 percent per year.

We find significant deterministic trends in integration for two out of the seven regions. Table.6 shows that North America, one of the regions without a time trend, indeed has a significant break in its integration measure in November - December 1995. Figure.2 clearly shows that up to 1995 there is a steep decreasing pattern in integration. After 1995 integration trends upwards. We repeat the tests for trends in integration for the period up to the break date and the period thereafter. The results are reported in Table.7 and show a significant negative time trend in integration from 1973 to 1995. This suggests that during this period North America becomes a less integrated region. As we argued before, this finding could be related to the fact that the weight of Japan increases substantially in the period before the Asian crisis in 1997. Also, not all countries are available for the full sample period. Whereas in 1973 the value-weighted world index consists mainly of the US, during the next 20 years more countries are added. After the break date we see a positive but insignificant trend in the integration measure of North America.

The findings for the ratio of global over systematic risk are similar. Again, we detect a significant break (according to models 1 and 3) in the series of North America at the end of 1995. When repeating the test for trends in the periods before and after the estimated break date, we find a significant negative time trend before 1995 and a positive but insignificant time trend thereafter (see Table.7). Additionally, while we find a significant upward trend in the ratio of global over systematic risk of the developed markets in the Asia - Pacific region, we also detect a break in the level of this series in September - October 1995.

In sum, our results provide strong evidence of increasing market comovements between the developed markets in Europe and Asia Pacific. Country residual risk, as a fraction of total risk, is decreasing over time, causing an upward trend in cross-country correlations. Furthermore, global factors are becoming more important relative to regional factors. As a result, the countries are becoming more integrated into the world market.

In contrast, while developed markets are becoming more correlated over time, for emerging markets this is clearly not the case. The fraction of total risk that is country-specific is not decreasing. Consequently, cross-country correlations either exhibit no significant time trends at all or even display a downward sloping trend. While for three out of the four emerging market regions global factors are becoming an increasingly important determinant of systematic risk and regional factors are becoming less important, there is vast fraction of country residual risk. As a result, these emerging markets are not becoming more integrated into the world market.

5.2 Commonality of trends

The previous section reports evidence of significant time trends in cross-country correlations and integration for a number of regions. These time trends indicate the speed of the increasing correlations and the speed of integration. An interesting question is whether different regions integrate into the world market at similar rates. Or, have cross-country correlations increased faster in Europe than in Asia? These kinds of questions can be addressed by testing for equality of time trends. To the best of our knowledge we are the first to formally test for differences in velocity by which different countries and regions integrate into the world market and differences in the rate at which cross-country correlations within different regions increase over time.

In order to test whether two estimated time trends are equal, we adopt the Vogelsang and Fransens (2005) procedure, and we use the t_2^* statistic they propose.[22] Critical values for the statistics are given in Table 1 of Vogelsang and Fransens (2005) and the 95 percent critical value is ± 5.22. In contrast to the tests for deterministic trends, this test does indeed require trend stationary time series. Also, if we test whether two regions have equal trends, we can only consider the overlapping sample period of the two regions. Consequently, in case of unequal lengths, we first have to check whether both regions have significant time trends during this overlapping sample period.

As a result, we end up with one hypothesis for common trends in correlations, one for common trends in integration and two hypotheses for common trends in the ratio of global over systematic variance. Table.8 reports the results. First, we find that cross-country correlations in the developed European markets increase at a significantly higher rate than the developed markets in the Asia Pacific region (0.66 percent versus 0.33 percent per year). The t_2^* statistic of 5.93 exceeds the 95 percent critical value of 5.22.

Next, we find that developed European markets integrate into the world market at a higher speed than the Asia Pacific markets. The t_2^* statistic of 4.07 exceeds the 90% critical value. On the other hand, the fraction of systematic variance due to global, rather than regional factors increases at similar rates for these two regions. Similarly, while there is an upward trend in the integration measure of the developed European markets, the integration of the Eastern European markets does not display any time trend. However, for both regions global factors are becoming increasingly

[22] Vogelsang and Fransens (2005) propose two statistics: the t_1^* and the t_2^* statistic. While they have a similar size, the latter has a higher power and we therefore use the t_2^* statistic. Unreported results show that our conclusions based on the t_1^* statistic are the same.

important over time, compared to regional factors. These two trends are indistinguishable, as can be seen in Table.8.

These results suggest that differences in the speed of integration are due to the changing importance of country-specific risk rather than due to changing relative importance of global and regional risk. In almost all regions we find that global factors are becoming more important over time and at similar speeds. This could be interpreted as a true global phenomenon. However, we only find upward trends in integration in two developed regions, for which the relative importance of country specific risk has decreased over the past decades.

5.3 Robustness check: average realized pairwise correlation

In order to derive our nonparametric measure for cross-country correlations, we have made a number of simplifying assumptions, as discussed in Section 2. In particular, we assume that all country returns within a certain region have the same factor exposures and the same idiosyncratic variances. In addition, we assume that the covariances between the country idiosyncratic returns are zero. These characteristics are allowed to vary across regions and over time. With these assumptions, we can avoid the estimation of individual factor exposures. Also, cross-sectional dispersion is a consistent estimator of the idiosyncratic variance, which allows us to combine cross-sectional and short time series data to derive monthly estimates of correlations.

In this section we investigate the robustness of our results for these assumptions by using an alternative nonparametric measure for cross-country correlations. For each month, we use daily excess returns to calculate realized pairwise correlations for all pairs of countries within a region. This measure is similar to that used in Ferreira and Gama (2004). The disadvantage of this measure for pairwise correlations is that we do not use a cross-sectional dimension for the estimation. Hence, the estimates are based only on 21 or 22 daily return observations. After estimation of the pairwise cross-country correlations we compute the equally weighted average correlation over all country-pairs within the region.

We estimate equally weighted average realized pairwise correlations for the seven regions in our sample. The sample period is the same as in previous sections and the results are presented in Table.9. First, Panel A shows that the time series averages of realized correlations are similar to those based on our correlation measure. For instance, the average monthly realized cross-country correlation within the developed European markets is 0.38 while based on our correlation measure it is 0.39 (which can be found in Table.2). The average realized correlations are slightly lower than the averages presented in Table.2 and the standard deviations are higher. This is likely to be related to the fact that the realized cross-country correlations can have negative values. Indeed, the minimum values of the realized correlations are negative for all regions. In contrast, our correlation measure, which is a variance ratio, can by construction only have positive values. Second, the ranking of regions based on the average realized cross-country correlations is almost the same as the ranking based on our correlation measure. The only difference is that according to Table.9, the average correlations in the developed European market region is larger than that in the Asia Pacific region, while in Table.2 it is the other way around.

Panel B presents the results of the Vogelsang (1998) tests for deterministic time trends. The results for the three developed market regions are similar to the results based on our correlation measure (see Table.5). Table.9 Panel B reports significant upward time trends for the average cross-country correlations in the developed European and Asia Pacific markets, while there is no significant time trend for the North American region. The estimated trend coefficients are higher than those presented in Table.5. Again, the trend coefficient for the developed European region is higher than that for Asia Pacific. Unreported results show that the hypothesis that the two trends are equal is rejected at a 10% level. Hence, the finding that cross-country correlations increase in Europe at a faster rate than in Asia Pacific is confirmed.

Table.9 Panel B also shows that, in contrast to the findings presented in Table.5, there is one significant time trend for the emerging market regions. The cross-country correlations within the Eastern European region display a significant upward time trend. Taking a further look at the time series of correlation measures reveals that in the second month of the sample period there is an extreme negative cross-country correlation estimate of -0.26. This negative correlation may have an important effect on the estimated time trend. Indeed, unreported results show that when the test for a trend is performed starting the third month, the trend coefficient is no longer significant. From an economic perspective it seems quite unlikely that in a certain month, the average pairwise correlation between all Eastern European markets is negative and of such a large magnitude. Hence, we conclude that the results for the emerging market regions based on the realized average pairwise correlations are similar to those based on the correlation measure proposed in this paper. We do not find clear evidence of time trends in cross-country correlations within these regions.[23]

In sum, our main findings are robust for using an alternative measure of realized monthly cross-country correlations. This alternative measure does not depend on the assumptions that the countries within a certain region have the same factor exposures and idiosyncratic variances.

[23] We also perform tests for breaks in the correlation series. We detect a significanty break for the emerging Asian markets. However, we do not find ant significant time trends before or after the estimated break date. We also detect a break in the series for Latin America. For this region we find a significant upward time trend in the first part of the sample period, before the estimated break date. However, after the break date and for the full sample period we do not find any significant trends. To be concise, these results are not reported in the paper.

However, this measure does not directly use the cross-sectional dimension and monthly pairwise correlations are based on only few daily return observations. In addition, the measure can result in substantial negative cross-country correlations. Given these two concerns, the results discussed above merely serve as a robustness check for the assumptions on factor exposures and variances.[24] The measure that we propose in Section 2 is our preferred measure.

6 Cross-regional correlation

In the previous section we analyze the average level of cross-country correlations within each region. In this section we use a similar approach to derive a measure of instantaneous cross-regional correlation. We estimate the pairwise correlation between two regional equally weighted indices, allowing for different exposures to the global factor and different regional risk factors. The excess return on an equally weighted regional index follows the two-factor model of eq. (8) and its variance is

$$Var(\tilde{r}_{EWat}) = \beta_{at}^2\sigma_{Wt}^2 + \gamma_{at}^2\sigma_{Lat}^2 + \frac{1}{N}\sigma_{\varepsilon at}^2. \tag{27}$$

The covariance between the indices of regions a and b equals:

$$Cov(\tilde{r}_{EWat}, \tilde{r}_{EWbt}) = \beta_{at}\beta_{bt}\sigma_{Wt}^2 + Cov(\gamma_{at}\tilde{L}_{at}, \gamma_{bt}\tilde{L}_{bt}) \tag{28}$$

and hence the correlation between the two regional indices is equal to:

$$Corr(\tilde{r}_{EWat}, \tilde{r}_{EWbt}) = \frac{\beta_{at}\beta_{bt}\sigma_{Wt}^2 + Cov(\gamma_{at}\tilde{L}_{at}, \gamma_{bt}\tilde{L}_{bt})}{\sqrt{\beta_{at}^2\sigma_{Wt}^2 + \gamma_{at}^2\sigma_{Lat}^2 + \frac{1}{N}\sigma_{\varepsilon at}^2}\sqrt{\beta_{bt}^2\sigma_{Wt}^2 + \gamma_{bt}^2\sigma_{Lbt}^2 + \frac{1}{N}\sigma_{\varepsilon bt}^2}}. \tag{29}$$

We estimate the returns due to regional factors for each region, $\gamma_{at}\tilde{L}_{at}$ and $\gamma_{bt}\tilde{L}_{bt}$, as the residuals of regression (19). As discussed in Section 2.2, in doing so we disregard $\frac{1}{N}\sigma_{\varepsilon at}^2$, since it is of second-order importance and is likely to be dominated by $\gamma_{at}^2\sigma_{Lat}^2$. In the estimates of the cross-regional correlations we leave out this term as well. We estimate the covariance between the regional factors using the Newey West (1987) adjustment for first order serial correlation. The orthogonalization regressions are performed for every two-month period and we therefore estimate cross-regional correlations for two-month periods as well. We estimate the common factor exposure and variance and the local factor variance as is explained in Section 2.2.

The sample period for which we analyze cross-regional correlations depends on the data availability for each region. We first consider the pairwise correlations between the developed market regions and between the emerging market regions separately. The developed market regions have

[24] Moreover, a measure of average correlation based on realized pairwise correlation does not lends itself easily in the type of decomposition we perform to generate our measures of integration.

the longest time span, from 1973 onwards, while all emerging market regions are available as of 1994. Furthermore, we examine the average cross-regional correlation for all seven regions starting in 1994. Figure.4 shows the average cross-regional correlations for these three groups. The figure indicates an upward trend in the average correlation between developed European markets, Asia Pacific and North America. The average correlation between the Eastern Europe, the Middle East and Africa, the emerging Asian markets and Latin America slopes up between 1994 and 1998, after which there seems to be a slight downward trend. The average correlation between all seven regions displays a positive slope with an upward shift in 1998.

Table.10 reports the summary statistics of the pairwise as well as average cross-regional correlations. First, the developed market regions are more highly correlated than the emerging market regions. Between 1973 and 2005 the average correlation between the developed market regions is 0.43. We also perform the calculations for this group for the same sample period as the emerging market regions, from 1994 to 2005. Unreported results show that in that period the average cross-regional correlation is 0.52. For the emerging market regions this is remarkably lower, namely 0.33. We find the same patterns for the pairwise correlations. In order to determine whether the observed trends in Figure.4 are statistically significant, we perform the Vogelsang (1998) test for deterministic trends. Table.9 shows that for the developed markets, two of the three pairwise correlation series as well as the average cross-regional correlations exhibit significant upward trends. This finding is confirmed for the sample period starting in 1994. In contrast, none of the pairwise correlations between emerging market regions have significant deterministic time trends and neither does the average cross-regional correlation. The upward trend in the average correlation between all seven regions is not statistically significant, as the t-PS_1 statistic of 1.51 is lower than the 95% critical value of 1.72.[25]

In conclusion, we detect clear differences between developed and emerging market regions. The developed European markets, Asia Pacific and North America are on average more highly correlated than the emerging market regions and their cross-regional correlations exhibit significant upward time trends. In contrast, the average correlation between emerging market regions does not show a significant time trend. This coincides with the results for the cross-country correlations. Hence, whereas both developed countries and developed regions are becoming more correlated over time,

[25] In addition, we test for the presence of shifts in deterministic trends using the Vogelsang (2001) method explained in Section 5. Unreported results show that the pairwise correlation series of Eastern Europe and the Middle East/Africa region has a significant level shift in March/April 1997. Whereas over the full 1994 to 2005 period we are not able to detect any time trends, we find a significant negative trend in the period after the break. We also detect breaks in the pairwise correlation series of Eastern Europe and Latin America and in the correlation between the Middle East/Africa and Latin America. During the periods before the estimated break dates in 2000 we find significant upward deterministic trends in both series, but after 2000 we do not detect any time trends.

cross-country and cross-region correlations in emerging markets do not display upward time trends.

7 Conclusions

In this paper, we investigate time patterns in global market linkages and comovements over short intervals. While some papers (Solnik and Roulet 2000, Baur, 2006) use cross-sectional dispersion to make inferences on correlations, we show that when factor exposures and volatilities vary over time, one always needs a time dimension in order to consistently estimate correlations. Hence, we propose a new nonparametric measure of instantaneous correlations between national equity markets, based on the combination of cross-sectional with time series data over short horizons. Our measure can be interpreted as the average level of correlations between the assets under consideration. It allows for monthly time variation in factor variances and exposures, while not requiring an explicit specification of the common factors. If we do specify the common factors, we can extract a measure of time-varying market integration, as the fraction of total risk due to global factors. This nonparametric measure of market integration is based solely on daily return data. It has a clear interpretation; a more integrated (segmented) market is dominated by global (local) factors and has an integration measure closer to one (zero). We show that it is straightforward to estimate monthly or two-monthly correlations and integration for a large cross-section of assets.

We examine global cross-market linkages for a sample of 24 developed countries and 26 emerging markets ranging from 1973 to 2005, which we subdivide into seven regions. We find that both correlations and integration measures are highly time-varying for all regions and we detect striking differences between developed and emerging market regions.

Our results show that the average level of comovements between developed markets is higher than between emerging markets. Furthermore, comovements between developed markets have significantly increased over the last few decades. Cross-country correlations within regions (Europe and Asia Pacific) as well as correlations between regions exhibit significant upward time trends. This indicates that the fraction of total risk that is country residual risk is declining. In addition, our results show that the global factor is becoming more important relative to the regional risk factors. As a result, the degrees of integration of developed European and Asian Pacific countries into the world market display significant upward time trends.

In contrast, comovements between emerging markets have not increased over time. Cross-country correlations either lack significant time trends (Eastern European, Asian, Latin American emerging markets) or even exhibit downward sloping time trends (Middle East/Africa). Cross-regional correlations across emerging markets do not exhibit significant time trends either. Furthermore, we do not detect any time trends in market integration of these four regions. Nevertheless, we find that the fraction of systematic variance due to global factors has increased for three out of the four emerging market regions. Hence, while emerging markets are not becoming more integrated in the world market due to their high country-specific risk, the systematic risk is increasingly of a global rather than a regional nature.

We find that whereas the developed European markets integrate faster into the world market than the Eastern European and Asia Pacific markets, the trends in the relative importance of global and regional factors are similar for these regions. This suggests that differences in the speed of integration are due to the changing importance of country-specific risk rather than due to changing relative importance of global and regional risk. The increasing relative importance of global factors is present in five out of seven regions and it seems to be a true global phenomenon. However, only the markets that also have decreasing country specific risk (developed European markets and Asia Pacific) are becoming more integrated into the world market.

The increasing level of comovements between developed markets has important implications for international investment strategies as it negatively affects the regions' diversification potential. Our evidence suggests as well that extending the investment set with emerging markets equities may deliver some of the benefits of international diversification previously offered by developed markets, although this issue merits further investigation.

Future research involves an investigation of the determinants of market integration and cross-country correlations. It is straightforward to perform a regression analysis of our time series of correlation and integration measures, and investigate their relationship to, amongst others, proxies for trade integration, financial market development, macro-economic development, or capital barriers.

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Table 1: Summary statistics daily excess returns

This table reports the summary statistics of daily excess returns for our sample of 50 countries, subdivided into seven regions, as well as for the value-weighted G50 index. The overall sample period runs from 3 January 1973 to 28 February 2005: a total of 8389 daily return observations. The first column reports the initial dates a country's equity index daily return becomes available. Returns have been adjusted for holidays. The mean and standard deviation are annualized assuming a 260-day year. Minimums and maximums are given as daily percentages. The column 'w_{av}' reports the average market value as a percentage of the total G50 market cap. The last two columns give the weights in the G50 market index at the beginning and at the end of the sample period.

	starting date	mean p.a.	stdev p.a.	min daily	max daily	w_{av}	w_{start}	w_{end}
Developed markets Europe								
Austria	03-Jan-73	6.86%	16.14%	-11.63%	9.22%	0.10%	0.03%	0.30%
Belgium	03-Jan-73	7.27%	16.65%	-11.16%	7.28%	0.55%	0.50%	0.89%
Denmark	03-Jan-73	9.07%	18.82%	-15.66%	17.28%	0.27%	0.13%	0.48%
Finland	01-Apr-88	11.13%	29.72%	-16.97%	15.45%	0.41%	0.12%	0.59%
France	03-Jan-73	8.78%	19.84%	-9.06%	9.28%	2.48%	1.06%	4.78%
Germany	03-Jan-73	5.96%	18.03%	-11.75%	7.87%	4.02%	3.29%	3.68%
Greece	01-Feb-90	13.92%	29.28%	-11.06%	16.63%	0.19%	0.05%	0.36%
Ireland	03-Jan-73	9.54%	19.14%	-15.51%	15.90%	0.15%	0.08%	0.36%
Italy	03-Jan-73	6.27%	23.09%	-9.65%	10.82%	1.39%	0.73%	2.54%
Luxembourg	03-Feb-92	10.10%	18.18%	-7.66%	10.60%	0.07%	0.02%	0.11%
Netherlands	03-Jan-73	8.79%	17.26%	-9.14%	8.01%	1.99%	1.74%	2.07%
Norway	01-Feb-80	8.34%	23.17%	-20.19%	10.81%	0.20%	0.21%	0.48%
Portugal	01-Feb-90	4.32%	16.72%	-7.05%	8.52%	0.19%	0.07%	0.24%
Spain	01-Apr-87	9.19%	19.74%	-10.23%	9.09%	1.23%	0.71%	2.11%
Sweden	01-Feb-82	12.12%	23.36%	-15.42%	11.34%	0.67%	0.29%	1.11%
Switzerland	03-Jan-73	7.28%	16.68%	-10.52%	6.77%	1.57%	0.94%	2.67%
UK	03-Jan-73	7.86%	18.87%	-13.54%	9.67%	8.21%	7.65%	9.14%
North America								
Canada	03-Jan-73	4.95%	14.58%	-10.91%	9.42%	2.43%	0.92%	3.15%
US	03-Jan-73	5.88%	15.92%	-18.72%	8.69%	45.47%	65.90%	43.05%
Developed markets Asia Pacific								
Australia	03-Jan-73	6.74%	20.11%	-26.17%	8.47%	1.35%	1.15%	2.18%
Hong Kong	03-Jan-73	10.69%	29.84%	-34.74%	16.83%	1.32%	0.79%	2.30%
Japan	03-Jan-73	4.47%	20.06%	-15.97%	12.21%	23.88%	14.78%	11.09%
New Zealand	01-Feb-88	8.52%	20.02%	-11.49%	9.46%	0.12%	0.07%	0.13%
Singapore	03-Jan-73	4.40%	23.48%	-23.13%	15.04%	0.47%	0.30%	0.53%

	starting date	mean p.a.	stdev p.a.	min daily	max daily	w_{av}	w_{start}	w_{end}
Eastern Europe								
Czech Republic	01-Dec-93	8.66%	23.37%	-6.57%	24.20%	0.03%	0.04%	0.03%
Hungary	03-Jul-95	22.80%	30.33%	-15.95%	12.34%	0.04%	0.01%	0.08%
Poland	01-Apr-94	4.80%	33.28%	-10.94%	18.53%	0.04%	0.03%	0.09%
Russia	01-Jul-94	35.80%	56.77%	-48.10%	35.20%	0.19%	0.04%	0.43%
Slovakia	03-Feb-97	5.85%	28.82%	-11.27%	8.74%	0.00%	0.01%	0.00%
Turkey	01-Dec-93	21.74%	57.14%	-23.70%	25.42%	0.12%	0.24%	0.09%
Middle East/Africa								
Israel	01-Feb-93	23.53%	66.20%	-10.69%	215.09%	0.12%	0.17%	0.15%
Morocco	01-Jan-96	9.19%	12.38%	-4.66%	5.03%	0.03%	0.02%	0.02%
Nigeria	03-Jul-95	20.08%	17.89%	-9.91%	10.82%	0.01%	0.01%	0.02%
South Africa	01-Feb-93	8.57%	22.84%	-13.16%	8.48%	0.54%	0.98%	0.50%
Zimbabwe	03-Jul-95	25.01%	53.80%	-93.31%	16.90%	0.01%	0.01%	0.00%
Emerging markets Asia								
China	02-Aug-93	10.64%	25.04%	-9.71%	9.74%	0.34%	0.01%	0.60%
India	03-Jul-95	7.51%	25.05%	-11.32%	9.64%	0.31%	0.57%	0.40%
Indonesia	01-May-90	2.03%	46.30%	-33.56%	46.39%	0.13%	0.13%	0.08%
Korea	01-Oct-87	8.12%	37.22%	-19.41%	21.55%	0.66%	0.24%	0.94%
Malaysia	02-Feb-87	7.08%	28.41%	-21.21%	25.78%	0.48%	0.21%	0.18%
Philippines	01-Dec-88	4.45%	27.71%	-9.27%	22.43%	0.13%	0.03%	0.04%
Taiwan	01-Jun-88	4.06%	34.37%	-10.51%	14.70%	0.95%	0.86%	0.88%
Thailand	02-Feb-87	10.91%	33.98%	-13.99%	18.01%	0.22%	0.04%	0.18%
Latin America								
Argentina	01-Sep-93	7.40%	34.59%	-28.58%	16.48%	0.12%	0.27%	0.03%
Brazil	01-Aug-94	14.84%	36.29%	-14.07%	15.80%	0.44%	0.47%	0.47%
Chile	01-Aug-89	15.85%	19.40%	-5.96%	9.12%	0.20%	0.07%	0.10%
Colombia	03-Jul-95	4.34%	18.71%	-6.00%	9.16%	0.03%	0.09%	0.02%
Mexico	01-Aug-89	15.45%	29.24%	-18.69%	15.31%	0.44%	0.08%	0.29%
Peru	01-Feb-94	10.32%	21.01%	-10.03%	10.34%	0.03%	0.04%	0.02%
Venezuela	01-Feb-90	21.23%	44.59%	-51.46%	22.75%	0.02%	0.01%	0.00%
G50 index	03-Jan-73	4.88%	11.94%	-9.23%	7.98%			

Table 2: Summary statistics of correlation and integration measures

The table reports summary statistics for average regional cross-country correlations, market integration (measured as the fraction of total variance due to global factors), and the ratio of global over systematic risk (measured as the fraction of global and regional variance due to global factors) for seven different regions. These ratios are based on a decomposition of total variance into global, regional and country-specific variance. Using daily excess returns on country indices, average regional cross-country correlations are estimated for every month. The other two variance ratios are estimated for every two-month period. The sample runs from January 1973 to February 2005 (386 monthly observations) for the three developed market regions, while it starts in December 1991 for the Eastern European markets, February 1993 for Middle East/Africa, February 1987 for emerging markets Asian markets and August 1989 for Latin America. The last column reports the number of estimates, N.

	mean	median	stdev	min	max	skew	kurt	N
Correlation								
Developed markets Europe	0.393	0.381	0.152	0.080	0.885	0.372	2.653	386
North America	0.796	0.816	0.097	0.408	0.975	-1.054	4.307	386
Developed markets Asia Pacific	0.432	0.427	0.135	0.137	0.814	0.273	2.805	386
Eastern Europe	0.315	0.299	0.120	0.098	0.714	0.739	3.254	135
Middle East/Africa	0.294	0.249	0.138	0.102	0.760	1.076	3.392	145
Emerging markets Asia	0.312	0.301	0.132	0.063	0.807	0.668	3.415	217
Latin America	0.357	0.344	0.126	0.094	0.840	0.624	3.735	187
Integration								
Developed markets Europe	0.208	0.190	0.137	0.002	0.655	0.845	3.335	193
North America	0.518	0.554	0.204	0.037	0.828	-0.554	2.370	193
Developed markets Asia Pacific	0.187	0.172	0.124	0.000	0.655	0.948	4.207	193
Eastern Europe	0.092	0.066	0.077	0.000	0.297	1.001	3.252	67
Middle East/Africa	0.066	0.050	0.051	0.000	0.187	0.625	2.277	72
Emerging markets Asia	0.090	0.074	0.080	0.000	0.341	1.255	4.409	108
Latin America	0.129	0.109	0.106	0.001	0.473	1.349	4.849	93
Global / systematic risk								
Developed markets Europe	0.472	0.484	0.194	0.012	0.834	-0.276	2.356	193
North America	0.637	0.721	0.230	0.051	0.937	-0.826	2.599	193
Developed markets Asia Pacific	0.395	0.395	0.198	0.000	0.869	0.081	2.602	193
Eastern Europe	0.266	0.268	0.174	0.000	0.672	0.335	2.280	67
Middle East/Africa	0.231	0.224	0.166	0.001	0.590	0.460	2.127	72
Emerging markets Asia	0.253	0.238	0.174	0.000	0.697	0.510	2.650	108
Latin America	0.337	0.359	0.205	0.003	0.832	0.206	2.198	93

Table 3: Autocorrelation structure of estimated average correlation and integration estimates

The table reports the autocorrelation at 1 to 12 lags of the following three variance ratios for each of the seven regions: average regional cross-country correlations, market integration (measured as the fraction of total variance due to global factors), and the ratio of global over systematic risk (measured as the fraction of global and regional variance due to global factors). The regional average cross-country correlations are estimated at a monthly frequency, while the other two variance ratios are estimated for two-month periods. The sample period starts in January 1973 for developed markets, in February 1987 for East-Asia, August 1989 for Latin America, December 1991 for Eastern Europe and February 1993 for the Middle East/Africa.

	Autocorrelation lag					
	1	2	3	4	6	12
Correlation						
Developed markets Europe	0.465	0.361	0.320	0.310	0.303	0.175
North America	0.245	0.206	0.124	0.143	0.146	-0.025
Developed markets Asia Pacific	0.329	0.250	0.170	0.194	0.200	0.110
Eastern Europe	0.232	0.244	0.221	0.035	0.096	0.084
Middle East/Africa	0.657	0.633	0.629	0.651	0.554	0.437
Emerging markets Asia	0.399	0.328	0.259	0.189	0.222	0.125
Latin America	0.304	0.243	0.268	0.159	0.094	0.189
Integration						
Developed markets Europe	0.506	0.413	0.484	0.349	0.294	0.179
North America	0.595	0.562	0.596	0.636	0.531	0.405
Developed markets Asia Pacific	0.377	0.323	0.334	0.161	0.176	0.114
Eastern Europe	0.275	0.301	0.158	0.202	0.047	-0.049
Middle East/Africa	0.050	-0.095	0.021	-0.130	-0.007	-0.278
Emerging markets Asia	0.073	0.232	0.275	0.041	0.142	-0.203
Latin America	0.506	0.404	0.410	0.418	0.258	0.105
Global / systematic risk						
Developed markets Europe	0.389	0.328	0.437	0.342	0.281	0.200
North America	0.653	0.622	0.643	0.672	0.600	0.444
Developed markets Asia Pacific	0.433	0.349	0.301	0.234	0.206	0.181
Eastern Europe	0.221	0.232	0.053	0.125	0.032	0.072
Middle East/Africa	0.039	-0.040	0.173	-0.055	0.102	-0.153
Emerging markets Asia	-0.005	0.220	0.146	0.146	0.153	-0.121
Latin America	0.554	0.543	0.543	0.459	0.358	0.205

Table 4: Unit root tests

The table presents the unit root tests for the time series of correlation and integration measures and the ratio of global over systematic risk for each of the seven regions. The Augmented Dickey Fuller test is performed with and without deterministic trend and with intercept with one lag. The p-values are given in brackets. Correlations are estimated at a monthly frequency, while the other two variance ratios are estimated for two-month periods. The sample period starts in January 1973 for developed markets, in February 1987 for East-Asia, August 1989 for Latin America, December 1991 for Eastern Europe and February 1993 for the Middle East/Africa.

	intercept		intercept and trend	
	t-stat	p-value	t-stat	p-value
Correlation				
Developed markets Europe	-2.39	(0.017)	-8.30	(0.000)
North America	-0.87	(0.333)	-10.22	(0.000)
Developed markets Asia Pacific	-2.06	(0.038)	-9.60	(0.000)
Eastern Europe	-1.27	(0.186)	-5.48	(0.000)
Middle East/Africa	-1.69	(0.087)	-3.58	(0.008)
Emerging markets Asia	-2.21	(0.026)	-6.59	(0.000)
Latin America	-1.78	(0.072)	-6.76	(0.000)
Integration				
Developed markets Europe	-2.19	(0.028)	-5.31	(0.000)
North America	-1.43	(0.143)	-4.41	(0.000)
Developed markets Asia Pacific	-2.56	(0.011)	-6.03	(0.000)
Eastern Europe	-1.17	(0.220)	-3.07	(0.035)
Middle East/Africa	-2.43	(0.016)	-6.32	(0.000)
Emerging markets Asia	-2.74	(0.007)	-5.47	(0.000)
Latin America	-1.90	(0.055)	-3.82	(0.004)
Global / systematic risk				
Developed markets Europe	-6.13	(0.000)	-8.12	(0.000)
North America	-3.97	(0.002)	-3.96	(0.012)
Developed markets Asia Pacific	-5.86	(0.000)	-6.87	(0.000)
Eastern Europe	-3.90	(0.004)	-4.69	(0.002)
Middle East/Africa	-6.08	(0.000)	-6.31	(0.000)
Emerging markets Asia	-5.69	(0.000)	-6.14	(0.000)
Latin America	-3.11	(0.029)	-4.10	(0.009)

Table 5: Test for deterministic trend, allowing for serial correlation

This table reports the estimated deterministic linear trends in the time series of correlation and integration measures and the ratio of global over systematic risk for the seven regions. The correlation measure is estimated at a monthly frequency and the other two variance ratios are estimated at a two-monthly frequency. The trend estimates are multiplied by 10^5. Below the estimated trend the Vogelsang (1998) t-PS^1 statistic is given in square brackets. This statistic is robust for various forms of serial correlation. The 95% critical value is ± 1.720. ** denotes significance at a 5% level. The appropriate value of constant b that is used is 0.716 (see Vogelsang 1998, Table II(i)). The sample period starts in January 1973 for developed markets, in February 1987 for East-Asia, August 1989 for Latin America, December 1991 for Eastern Europe and February 1993 for the Middle East/Africa.

	Correlation	Integration	Global / systematic risk
Developed markets Europe	52.574**	112.887**	166.070**
	[3.280]	[3.098]	[2.848]
North America	1.504	-83.836	-121.414
	[0.117]	[-0.220]	[-0.221]
Developed markets Asia Pacific	27.845**	90.286**	175.477**
	[2.083]	[2.861]	[2.202]
Eastern Europe	4.585	126.084	352.818**
	[0.078]	[1.395]	[1.919]
Middle East/Africa	-253.184	-8.568	243.517
	[-1.332]	[-0.244]	[1.512]
Emerging markets Asia	-26.346	22.313	107.567**
	[-0.381]	[0.643]	[2.040]
Latin America	-51.365	184.097	494.678**
	[-1.248]	[1.104]	[1.852]

Table 6: Test for a shift in intercept and/ or in deterministic trend, allowing for serial correlation

This table reports the results of tests for shifts in intercepts and/ or deterministic linear trends in the time series of correlation and integration measures and the ratio of global over systematic risk. First, the break date is estimated using the extremum statistic of Andrews (1993), using 10% trimming. Then, we employ the Vogelsang (2001) procedure to test for a shift in intercept (model 1), in linear trend (model 2) and in intercept and trend (model 3). These tests are robust for various forms of serial correlation. We report the estimated break dates and the PS^1 statistics (in square brackets). The 95% critical values are ±4.205, ±3.387 and ±5.312 for models 1 to 3 respectively. These values and the appropriate value of constant b can be found in Vogelsang (2001) Table 4. ** denotes significance at the 5% level. Results are reported for the seven regions.

	Model 1	Model 2	Model 3
Correlation			
Developed markets Europe	Feb-92	Jul-00	Jul-92
	[1.093]	[0.022]	[1.873]
North America	Jun-96	Nov-01	Jun-96
	[0.228]	[0.025]	[0.179]
Developed markets Asia Pacific	Jul-97	Apr-96	Jan-83
	[0.328]	[0.322]	[1.090]
Eastern Europe	Nov-03	Jan-95	Feb-95
	[0.117]	[0.320]	[0.494]
Middle East/Africa	Jun-95**	Nov-96**	Jun-95**
	[125.178]	[8.840]	[132.440]
Emerging markets Asia	Nov-88	Dec-88**	Dec-88
	[3.941]	[4.072]	[4.084]
Latin America	Jun-97	Jun-03	Sep-01
	[0.201]	[0.018]	[0.752]
Integration			
Developed markets Europe	Jul/Aug 91	Jul/Aug 00	Jan/Febr 92
	[1.326]	[0.033]	[2.568]
North America	Nov/Dec 95**	Jul/Aug 92	Nov/Dec 95
	[6.609]	[1.411]	[4.028]
Developed markets Asia Pacific	Jul/Aug 92	Jul/Aug 90	Jul/Aug 92
	[1.122]	[0.994]	[1.574]
Eastern Europe	Nov/Dec 98	Jul/Aug 03	Nov/Dec 98
	[0.101]	[0.000]	[0.401]
Middle East/Africa	Jul/Aug 97	Nov/Dec 99	Jul/Aug 95
	[0.784]	[0.237]	[0.014]
Emerging markets Asia	Mar/Apr 03	May/Jun 02	Mar/Apr 03
	[0.596]	[0.446]	[0.532]
Latin America	Nov/Dec 96	Jul/Aug 98	Jul/Aug 97
	[0.499]	[0.063]	[0.127]

	Model 1	Model 2	Model 3
Global / systematic risk			
Developed markets Europe	Jul/Aug 91	Jan/Feb 82	Nov/Dec 91
	[1.961]	[0.485]	[1.830]
North America	Nov/Dec 95**	Jul/Aug 92	Sep/Oct 95**
	[8.344]	[2.900]	[6.976]
Developed markets Asia Pacific	Sep/Oct 95**	Jan/Feb 91	Nov/Dec 89
	[4.281]	[2.414]	[4.235]
Eastern Europe	Nov/Dec 98	Jan/Feb 98	Nov/Dec 98
	[0.093]	[0.918]	[1.714]
Middle East/Africa	Jul/Aug 97	Nov/Dec 98	Jul/Aug 97
	[1.765]	[2.711]	[3.121]
Emerging markets Asia	Mar/Apr 03	Sep/Oct 02	Mar/Apr 03
	[0.092]	[0.077]	[0.088]
Latin America	Nov/Dec 96	Jul/Aug 98	Nov/Dec 96
	[0.662]	[0.043]	[0.658]

Table 7: Test for deterministic trends before and after break dates

This table reports the Vogelsang (1998) tests for deterministic trends for subsample periods. We only consider series that have significant breaks in the level, slope or both (based on models 1, 2 and 3 of the Vogelsang (2001) methodology). The break date is estimated using the extremum statistic of Andrews (1993), using 10% trimming. We perform tests for the sample periods before and after the estimated break date, with a minimum of 30 observations. This table reports the estimated deterministic trends for the subsample periods. These estimates are multiplied by 10^5. Below the estimated trend the Vogelsang (1998) t-PS^1 statistic is given in square brackets. The 95% critical value is ± 1.720. ** denotes significance at a 5% level.

	estimated break date	subsample period	trend$\cdot 10^5$
Correlation			
Emerging markets Asia	Dec-88	Jan-89 to Feb-05	33.233
			[1.095]
Middle East/Africa	Jun-95	Jul-95 to Feb-05	-39.422**
			[-3.155]
	Nov-96	Feb-93 to Nov-96	-736.224
			[-1.207]
		Dec-96 to Feb-05	-41.848**
			[-2.411]
Integration			
North America	Nov/Dec 95	Jan-73 to Dec 95	-326.262**
			[-3.048]
		Jan-96 to Feb-05	179.908
			[0.611]
Global / systematic risk			
North America	Nov/Dec 95	Jan-73 to Dec 95	-422.664
			[-3.761]**
		Jan-96 to Feb-05	323.490
			[1.280]

Table 8: Test for common deterministic trends

This table reports the results for the tests for equality of deterministic trends using the Vogelsang and Fransens (2005) t_2^* test statistic. The test requires that the series have significant trends for the overlapping sample period and that they are trend-stationary. The critical values can be found in Table 1 of Vogelsang and Fransens (2005), the 95% critical value is ± 5.222. We test hypotheses of the form H_0: $\text{trend}_1 = \text{trend}_2$ where trend_1 and trend_2 are the estimated deterministic trends of two regions. The table reports the null hypothesis, the relevant sample period, the estimated trends of both regions (multiplied by 10^5) and the t_2^* statistic (in square brackets). ** and * denote significance at the 5% and 10% levels. These tests are performed for correlation and integration series, as well as for the ratio of global risk over total systematic risk.

H_0	sample period	$\text{trend}_1(\cdot 10^5)$	$\text{trend}_2(\cdot 10^5)$	t_2^*
Correlation				
trend devEur = trend AsiaPac	Jan-73 to Feb-05	52.574	27.845	[5.927]**
Integration				
trend devEur = trend AsiaPac	Jan-73 to Feb-05	112.887	90.286	[4.069]*
Global / systematic risk				
trend devEur = trend AsiaPac	Jan-73 to Feb-05	166.070	175.477	[1.623]
trend devEur = trend EastEur	Jan-94 to Feb-05	431.791	352.818	[-1.091]

Table 9: Robustness check: average realized pairwise correlations

This table reports the results for an alternative measure of monthly cross-country correlations. For each region, the monthly pairwise realized correlations are calculated, based on the daily excess returns within the month. Then, an equally weighted average is calculated over all pairwise correlations within the region for that month. The sample is the same as in previous tables. The table reports the summary statistics and the results of the Vogelsang (1998) test for deterministic trends. The trend estimates are multiplied by 10^5. The last column shows the Vogelsang (1998) t-PS^1 statistic is given in square brackets. The 95% critical value is ± 1.720. ** denotes significance at a 5% level.

	mean	median	stdev	min	max	skew	kurt	$\text{trend}(\cdot 10^5)$	t-PS^1
Dev. mkts Europe	0.381	0.385	0.161	-0.021	0.912	0.097	2.702	78.878	[3.334]**
North America	0.567	0.610	0.196	-0.208	0.914	-0.869	3.518	9.417	[0.369]
Dev. mkts Asia Pacific	0.265	0.261	0.174	-0.122	0.804	0.305	2.868	67.854	[3.332]**
Eastern Europe	0.157	0.138	0.131	-0.267	0.522	0.168	3.107	158.751	[1.882]**
Middle East/Africa	0.031	0.025	0.106	-0.261	0.400	0.631	4.259	-38.581	[-1.411]
Emerging mkts Asia	0.169	0.163	0.125	-0.156	0.626	0.541	3.493	26.799	[0.884]
Latin America	0.176	0.160	0.161	-0.201	0.661	0.510	3.269	97.347	[0.990]

Table 10: Cross-regional correlations

The table reports summary statistics and tests for trends for cross-regional correlations. The average cross-regional correlations are estimated every two months nonparametrically, using daily excess returns. Different regions are allowed to have different exposures to the global factor and different regional factors. The table reports pairwise correlations as well as the average correlation between the developed market regions between January 1973 and February 2005. The correlations between the emerging market regions and the average correlations between all seven regions are estimated for the period from January 1994 to February 2005. Next to the summary statistics the table reports estimated deterministic trends using the Vogelsang (1998) method. These trend estimates are multiplied by 10^5. Below the estimated trend the Vogelsang (1998) t-PS[1] statistic is given in square brackets. The 95% critical value is ± 1.720. ** denotes significance at a 5% level.

Developed market regions: Jan 73 - Febr 05					**All regions: Jan 94 - Febr 05**		
	devEur - NorthAm	devEur - AsiaPac	AsiaPac - NorthAm	average			
mean	0.43	0.50	0.35	0.43	mean	0.42	
median	0.45	0.53	0.38	0.43	median	0.43	
stdev	0.23	0.20	0.21	0.18	stdev	0.13	
N	193	193	193	193	N	67	
trend($\cdot 10^5$)	105.77	95.92	99.68	100.45	trend($\cdot 10^5$)	362.23	
t-PS[1]	[1.335]	[1.788]**	[2.496]**	[2.391]**	t-PS[1]	[1.505]	
Emerging market regions: Jan 94 - Febr 05							
	EastEur - MideastAfr	EastEur - emAsia	EastEur - LatinAm	emAsia - MideastAfr	LatinAm - MideastAfr	LatinAm - emAsia	average
mean	0.29	0.35	0.37	0.29	0.30	0.36	0.33
median	0.29	0.38	0.36	0.32	0.34	0.40	0.31
stdev	0.23	0.22	0.24	0.21	0.23	0.19	0.16
N	67	67	67	67	67	67	67
trend($\cdot 10^5$)	457.65	491.32	642.96	63.03	296.58	177.00	354.76
t-PS[1]	[0.832]	[1.519]	[1.306]	[0.384]	[0.538]	[0.785]	[0.946]

Figure 1: Nonparametric estimates of time-varying cross-country correlations

The figure plots the monthly regional average cross-country correlation estimates based on daily excess returns of 50 countries. We consider seven regions, that have different sample lengths. The sample period starts in January 1973 for developed markets, in February 1987 for East-Asia, August 1989 for Latin America, December 1991 for Eastern Europe and February 1993 for the Middle East/Africa. The bold line represents the 12-month moving average.

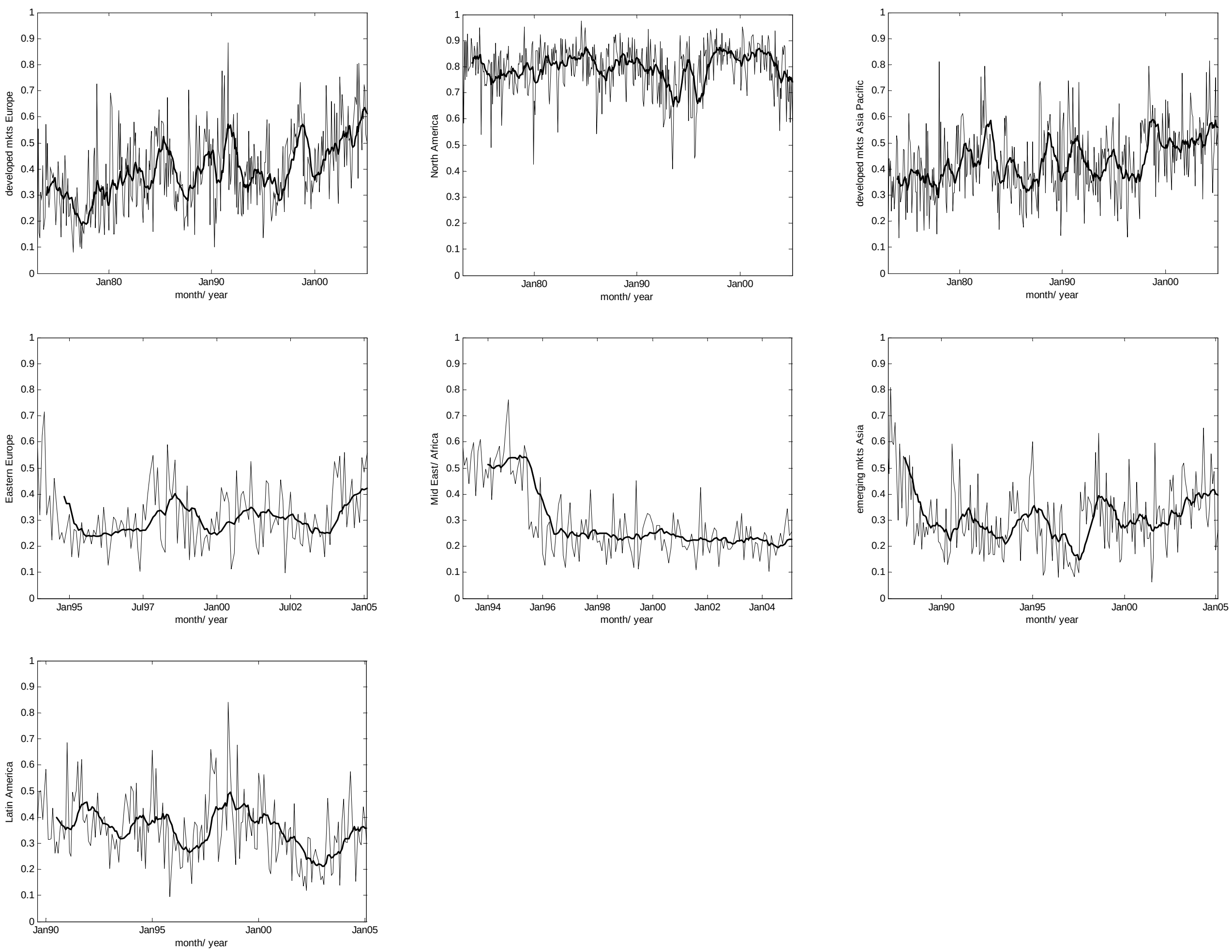

Figure 2: Variance decompostion: global, regional and country risk

The figure displays a decompositions of the total country variance into variance due to global factors, regional factors and country residual variance. The global factor is the value-weighted G50 index. The regional factors are the value-weighted regional index returns that have been orthogonalized to the global index return. Country risk is the residual risk. Factor variances and exposures are allowed to change over time and are estimated using daily excess returns over two-month periods for 50 countries from seven different regions. The sample period starts in January 1973 for developed markets, in February 1987 for the emerging Asian markets, August 1989 for Latin America, December 1991 for Eastern Europe and in February 1993 for the Midle East/Africa. The areas are based on 12-month moving averages. The dark grey area represents the fraction of total variance due to global factors. This is a measure of the integration of the countries of that region into the world market. The dark grey and white areas combined represent the fraction of total variance due to systematic risk, which is equal to the average cross-country correlations within the region.

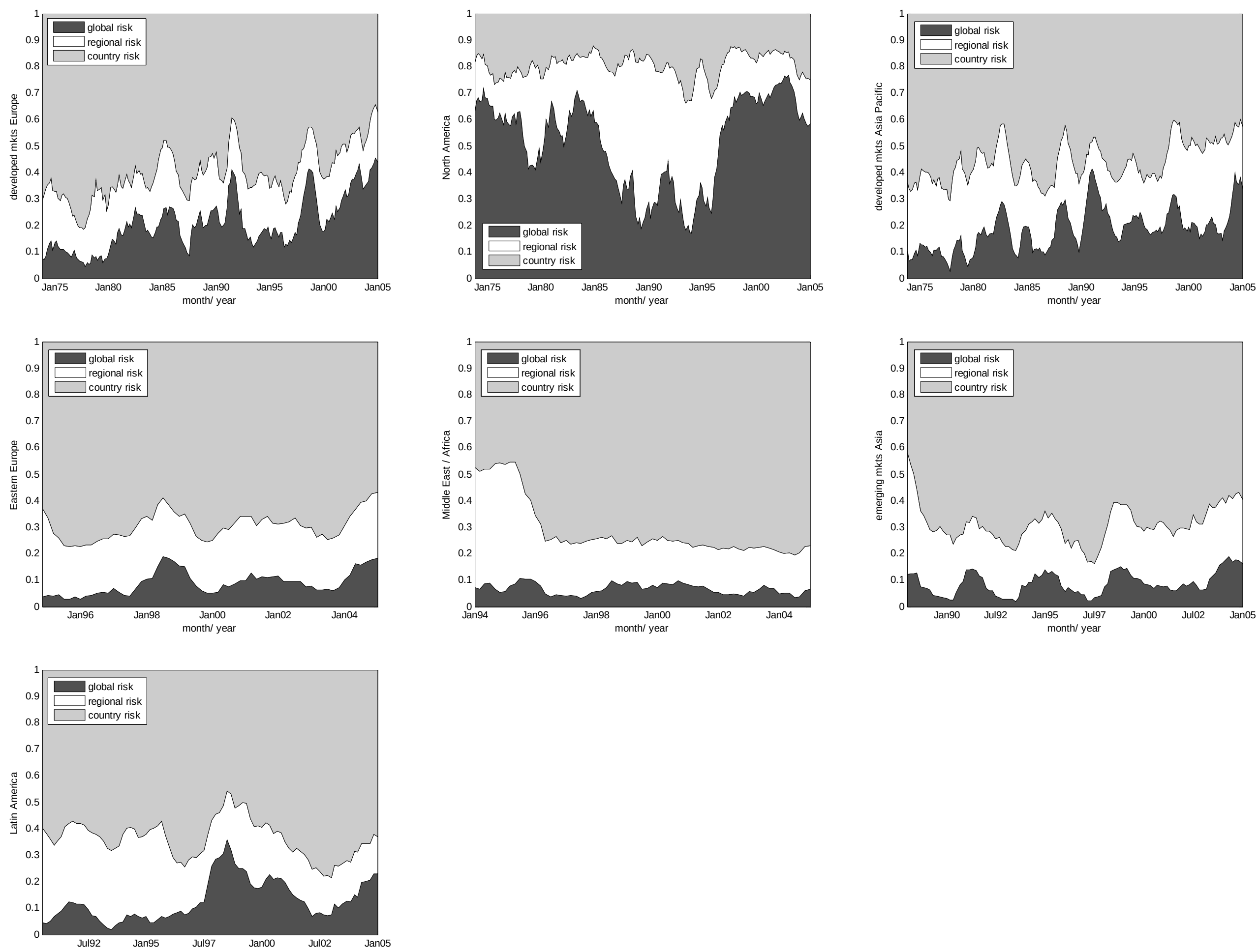

Figure 3: Correlation versus cross-sectional dispersion for developed markets Europe

The upper panel shows the one-month estimates of the average correlation between the developed markets in Europe. The lower panel shows the one-month estimates of the average country residual risk of the countries in this region, based on cross-sectional dispersion. The bold lines represent the 12-month moving averages.

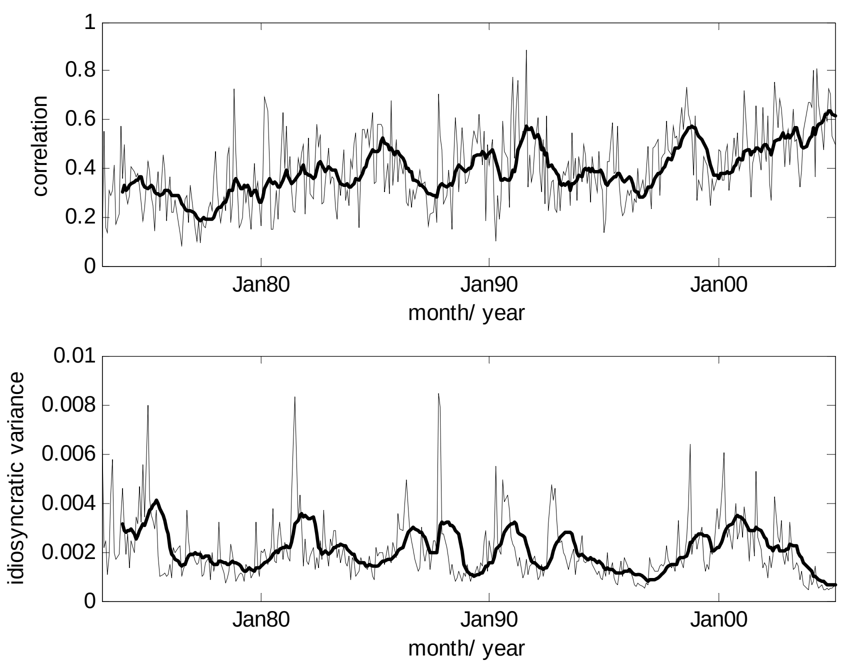

Figure 4: Time-varying average cross-regional correlations

The first plot displays two-month estimates of average cross-regional correlations for the three developed market regions starting January 1973. The second plot displays cross-regional correlations of the four emerging market regions and starts in January 1994. The third plot displays the average correlations between all seven regions, starting in January 1994. Different regions can have different exposures to the global factor and different regional factors.