The structure of international stock market returns

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Abstract

The behavior of international stock market returns in terms of their distributional properties, serial dependence, long-memory and conditional volatility is examined. A factor analysis is employed to identify the underlying dimensions of the returns. The analysis reveals the existence of meaningful factors when these are estimated from the empirical properties of a large set of international equity indices. Furthermore, the factor scores discriminate very well the stock markets according to size and level of development.

Keywords: International stock markets; Serial dependence; Long-memory; Conditional volatility; Factor analysis.

1 Introduction

International stock return comovements has become an important research area in recent years. For instance, financial economists are interested in understanding how expanding capital and trade movements affect the dynamics of stock returns across different markets. Investors need to understand international stock market relationships for portfolio diversification and risk management purposes. This interest has motivated researchers to develop statistical methods to study the behavior of stock prices and to identify the sources of return covariation. Among these methods one can find correlation analysis (Lin et al., 1994; Longin and Solnik, 1995; Karolyi and Stulz, 1996), vector error correction and cointegration analysis (Bessler and Yang, 2003; Syriopoulos, 2004; Tahai et al., 2004), factor models (Engel and Susmel, 1993) and cluster analysis (Caiado and Crato, 2010).

In this study, international stock return comovements are investigated using an alternative, yet simple, approach. We describe stock returns in terms of their empirical properties, and employ factor analysis to identify the underlying dimensions of these properties. Factor analysis is, of course, one of the widely used dimension reduction methods to capture

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common dynamic features in multiple asset returns. However, in the traditional statistical factor analysis, the factors are extracted from the covariance matrix of the historical returns assuming that the data have no serial correlation, and this assumption is often violated in high-frequency financial asset returns. To avoid this problem, some researchers suggest the use of a parametric model (e.g., a VARMA model) to remove the time dependency of the observations, and apply factor analysis to the residual series. Nevertheless, as pointed out by Tsay (2005) among others, the correlations of the residual series are often very close to the correlations of the original data, and therefore this procedure may be redundant. Our study differs from previous work in two ways. First, we estimate the latent or unobserved factors not from the observed returns but from their empirical properties such as mean, standard deviation, skewness, kurtosis, linear and nonlinear dependence, long-memory, conditional volatility and asymmetric effects. In this case, one may use stock or index returns with high frequency without imposing any restriction about the dynamic dependence of observations on factor analysis. An empirical application of this approach to a large set of international equity indices suggests the existence of meaningful factors in the derived solutions. Second, the factor loadings, which in our study represent the correlation of the properties of stock returns with the derived factors, are used to compute factor scores for every market under consideration. These factor scores are then used to identify clusters of markets and multivariate outliers. We show that these scores discriminate well international stock markets according to size and level of development.

The outline of the article is as follows. Section 2 presents the empirical properties of stock returns that are used as inputs to the factor analysis. The univariate statistics that are obtained for a set of international equity indices are also discussed. Section 3 provides a description of the statistical methodology, the factor solutions, and the factor scores. Section 4 concludes the paper.

2 Empirical properties of international stock returns

2.1 Distributional properties of returns

Let P_t denote the price of an asset at time t. The continuously compounded return (or log return) from $t-1$ to t is defined as $r_t = \ln(P_t/P_{t-1})$. Standard univariate descriptive statistics of asset returns include the mean, the standard deviation, the skewness and the excess kurtosis of returns. The mean is computed as the average log return. The standard deviation, or unconditional volatility, is a measure of dispersion in the return series and is usually considered as a proxy of asset risk. The skewness is the coefficient of asymmetry of the distribution of the return series. The kurtosis measures the “fatness” of the tails of the returns distribution. If the data are normally distributed, the skewness and excess kurtosis should be close to zero. A distribution with positive excess kurtosis has heavy tails, whereas a distribution with negative excess kurtosis has short tails. In many empirical studies, the distribution of log returns usually has fatter tails than the normal distribution, which means that extreme events occur more often than would be predicted from a normal distribution. For instance, it is well known that emerging market returns depart from the normal distribution (e.g., Harvey, 1995; Bekaert and Harvey, 1997).

2.2 Short-term dependence

The short-term serial dependence describes the low-order correlation structure of a time series. In this study, the presence of short-term linear dependence in stock prices is examined by the autocorrelations of the return series. For financial data, the autocorrelations of returns are typically zero or very close to zero, in consonance with the random walk or martingale hypothesis. However, stock returns often do exhibit some serial correlation (e.g., Lo and MacKinlay, 1988).

The presence of nonlinear dependence and possible autoregressive heteroskedasticity effects is judged by the autocorrelations of squared or absolute returns. In contrast to the autocorrelations of returns, which are typically not significant, the autocorrelations of squared or absolute returns are generally positive and significative for a substantial number of lags. This stylized fact is known as *volatility clustering*, meaning that large (small) volatility is often followed by large (small) volatility. In addition, the autocorrelations of absolute returns are generally higher than the autocorrelations of squared returns, especially for stock market indices (Franses and van Dijk, 2000).

The hypothesis of no autocorrelation up to order m in the returns (absolute returns) is tested using the Ljung-Box modified $Q(m)$-statistic:

$$Q(m) = n(n+2)\sum_{s=1}^{m}\frac{\widehat{\rho}_s^2}{n-s}, \tag{1}$$

where $\widehat{\rho}_s$ denotes the sample autocorrelation of the returns (absolute returns) at lag s. The choice of $m \approx \ln(n)$ may be appropriate for better power properties (Tsay, 2005).

2.3 Long-memory

Many time series exhibit long-memory or long-range dependence behavior. More formally, a stationary process x_t exhibits long-memory with memory parameter d if its spectral density function $f(\omega)$ satisfies

$$f(\omega) \sim C\omega^{-2d}, \quad \text{as} \quad \omega \to 0, \tag{2}$$

where C is a positive finite constant and ω denotes the frequency. When $d < 0.5$ its autocorrelation function ρ_k decays at a hyperbolic rate, i.e.

$$\rho_k \sim C_\rho k^{2d-1}, \tag{3}$$

where C_ρ is a constant with respect to k. If $0 < d < 0.5$, the process has long memory. If $d = 0$, the process has no memory. If $-0.5 < d < 0$, the process has intermediate memory. For $d > 0.5$, the process is no longer covariance stationary.

Of particular interest in financial economics is the long memory behavior of absolute stock returns and squared returns. Many empirical studies have noticed very slowly decaying autocorrelations for absolute (or squared) returns. As noted by Ding et al. (1993) and Granger and Ding (1996), the evidence of long memory is stronger for $|r_t|$ than for r_t^2. Using price series from various stock markets and commodity prices, Granger and Ding (1996) showed that $|r_t|$ has the properties of an $I(d)$ process with d values around 0.45.

2.4 Conditional volatility

Many time-varying volatility models have been proposed to capture the so-called "asymmetric volatility" effect where volatility tends to be higher after a negative return shock than a positive shock of the same magnitude (see, e.g., Bollerslev et al., 1992). A univariate volatility model commonly used to allow for asymmetric shocks to volatility is the threshold GARCH (or TGARCH) model (see Glosten et al., 1993; Zakoian, 1994). The simple TGARCH(1,1) model assumes the form

$$\begin{aligned} \varepsilon_t &= \sigma_t z_t, \\ \sigma_t^2 &= \omega + \beta\sigma_{t-1}^2 + \alpha\varepsilon_{t-1}^2 + \gamma\varepsilon_{t-1}^2 d_{t-1}, \end{aligned} \tag{4}$$

where $\{z_t\}$ is a sequence of independent and identically distributed random variables with zero mean and unit variance; $d_t = 1$ if ε_t is negative, and $d_t = 0$ otherwise. The volatility may either diminish ($\gamma < 0$), rise ($\gamma > 0$), or not be affected ($\gamma \neq 0$) by negative shocks or "bad news" ($\varepsilon_{t-1} < 0$). Good news have an impact of α while bad news have an impact of $\alpha + \gamma$. The persistence of shocks to volatility can be given by $\alpha + \beta + \gamma/2$.

2.5 Empirical results

The empirical properties of stock returns listed above were calculated for 46 free float-adjusted market capitalization equity indices constructed by Morgan Stanley Capital International (MSCI). The dataset includes 23 markets classified as developed[1] and 23 markets classified as emerging[2]. The index prices are expressed in local currency and cover the period from January 1995 to December 2009, in a total of 3,914 daily observations.

Stock returns are characterized by 10 empirical properties: mean, standard deviation (*stdev*), skewness (*skew*), and kurtosis (*kurt*) of the return distribution; the Ljung-Box Q-statistics for the hypothesis of no autocorrelations up to order m in the returns (*qstat*) and absolute returns (*qstat2*), where m is the largest integer less or equal to $\ln(n)$; the long

[1] Australia (AUST), Austria (AUS), Belgium (BEL), Canada (CAN), Denmark (DEN), Finland (FIN), France (FRA), Germany (GER), Greece (GRE), Hong Kong (HK), Ireland (IRE), Italy (ITA), Japan (JAP), Netherlands (NET), New Zealand (NZ), Norway (NOR), Portugal (POR), Singapore (SING), Spain (SPA), Sweden (SWE), Switzerland (SWI), United Kingdom (UK) and United States (US).

[2] Argentina (ARG), Brazil (BRA), Chile (CHI), China (CHI), Czech Republic (CR), Colombia (COL), Egypt (EGY), Hungary (HUN), India (IND), Indonesia (INDO), Israel (ISR), Korea (KOR), Malaysia (MAL), Mexico (MEX), Morocco (MOR), Peru (PER), Philippines (PHI), Poland (POL), Russia (RUS), South Africa (SA), Taiwan (TAI), Thailand (THA) and Turkey (TUR).

Market	*mean*	*stdev*	*skew*	*kurt*	*qstat*	*qstat2*	d	α	β	γ
Australia	0.024	1.045	-0.418	9.07	20.1*	2047.0*	0.197	0.011	0.926	0.103
Austria	0.007	1.453	-0.349	13.34	16.5**	4581.5*	0.240	0.050	0.880	0.095
Belgium	0.007	1.346	-0.588	14.15	86.4*	3351.3*	0.239	0.061	0.882	0.094
Canada	0.032	1.265	-0.636	11.56	24.2*	2790.7*	0.211	0.033	0.923	0.069
Denmark	0.036	1.280	-0.332	9.03	25.3*	2446.6*	0.222	0.050	0.901	0.072
Finland	0.031	2.365	-0.360	8.97	22.1*	1496.8*	0.188	0.054	0.932	0.025
France	0.022	1.440	-0.063	7.71	50.8*	1829.7*	0.183	0.013	0.923	0.104
Germany	0.018	1.544	-0.101	7.38	25.2*	2429.0*	0.194	0.031	0.903	0.109
Greece	0.017	1.754	-0.118	7.07	76.2*	1624.2*	0.201	0.093	0.855	0.084
Hong-Kong	0.016	1.719	0.026	11.43	25.2*	1997.5*	0.220	0.035	0.919	0.078
Ireland	-0.013	1.610	-0.722	15.67	39.5*	3430.5*	0.219	0.054	0.902	0.068
Italy	0.011	1.426	-0.062	7.92	53.8*	2079.0*	0.200	0.048	0.904	0.083
Japan	-0.013	1.431	0.133	8.44	22.6*	1626.7*	0.189	0.029	0.904	0.099
Netherlands	0.016	1.454	-0.182	8.00	60.3*	3086.6*	0.217	0.028	0.904	0.114
Norway	-0.004	1.145	-0.632	18.23	23.0*	1306.4*	0.187	0.046	0.920	0.046
New Zealand	0.023	1.580	-0.564	10.05	18.2**	3370.9*	0.220	0.065	0.863	0.088
Portugal	0.016	1.121	-0.278	11.42	78.6*	1796.2*	0.210	0.059	0.913	0.054
Singapore	0.007	1.439	0.030	8.46	19.5**	1729.3*	0.208	0.063	0.890	0.084
Spain	0.040	1.469	-0.132	7.83	48.2*	2088.5*	0.196	0.036	0.906	0.096
Sweden	0.035	1.684	0.091	6.40	15.2	1609.4*	0.187	0.033	0.911	0.093
Switzerland	0.025	1.245	-0.102	8.56	56.0*	2717.7*	0.227	0.017	0.899	0.134
United Kingdom	0.014	1.215	-0.174	9.40	95.3*	2691.6*	0.207	0.001	0.930	0.120
United States	0.024	1.282	-0.214	11.13	46.8*	2730.4*	0.197	0.000	0.924	0.133
Average	0.017	1.448	-0.261	10.05	41.26	2385.1	0.207	0.040	0.905	0.089
Argentina	0.051	2.356	-0.066	9.49	18.5*	1673.7*	0.229	0.059	0.840	0.138
Brazil	0.062	2.134	0.333	13.42	54.2*	2065.3*	0.220	0.023	0.869	0.140
Chile	0.027	1.144	0.331	13.08	164.2*	1574.2*	0.239	0.088	0.826	0.102
China	-0.002	2.141	0.035	8.07	67.6*	1748.9*	0.212	0.070	0.886	0.079
Colombia	0.070	1.476	0.178	14.63	236.6*	1942.8*	0.188	0.343	0.588	0.088
Czech Republic	0.034	1.595	-0.359	12.17	28.7*	2201.8*	0.232	0.111	0.855	0.059
Egypt	0.085	1.852	-0.251	7.94	118.4*	1168.8*	0.210	0.110	0.889	0.002
Hungary	0.067	2.022	-0.379	11.20	56.7*	1633.5*	0.242	0.093	0.844	0.070
India	0.042	1.764	-0.139	8.31	68.2*	1411.7*	0.210	0.076	0.823	0.132
Indonesia	0.048	2.175	-0.130	12.28	84.2*	1287.9*	0.216	0.092	0.838	0.108
Israel	0.034	1.467	-0.354	7.84	19.5**	870.0*	0.158	0.031	0.940	0.043
Korea	0.026	2.168	0.020	6.59	45.0*	1424.2*	0.176	0.033	0.937	0.052
Malaysia	0.009	1.615	0.763	44.72	61.0*	3089.0*	0.278	0.075	0.881	0.088
Mexico	0.065	1.638	0.099	7.88	48.4*	977.5*	0.183	0.027	0.890	0.125
Morocco	0.036	0.850	-0.063	9.03	297.4*	1687.9*	0.249	0.279	0.710	0.023
Peru	0.060	1.841	-0.136	9.62	54.7*	2066.3*	0.206	0.086	0.873	0.059
Philippines	-0.005	1.651	0.350	12.33	97.2*	660.6*	0.170	0.096	0.794	0.108
Poland	0.026	1.858	-0.115	5.16	35.0*	873.4*	0.171	0.058	0.905	0.040
Russia	0.052	3.260	-0.367	12.63	39.2*	1920.5*	0.234	0.126	0.851	0.047
South Africa	0.036	1.355	-0.413	7.81	53.8*	1460.6*	0.203	0.052	0.892	0.082
Taiwan	0.000	1.716	-0.024	5.03	23.4*	572.6*	0.141	0.027	0.931	0.066
Thailand	-0.017	2.092	0.661	13.32	93.0*	947.0*	0.201	0.071	0.873	0.083
Turkey	0.142	2.772	0.034	7.53	22.0*	883.4*	0.181	0.071	0.890	0.043
Average	0.041	1.867	0.000	11.27	77.7	1484.4	0.206	0.091	0.853	0.077

Table 1: Empirical properties of international stock market daily returns. * (**) indicates rejection of the hypothesis of no autocorrelation at the 1% (5%) level.

memory parameter d; and the TGARCH parameters (α, β and γ). Table 1 presents the calculated properties for daily percentage returns. The estimator of the long-memory parameter is based on the frequency domain Gaussian approach of Robinson (1995). The estimated parameters of the threshold GARCH(1,1) model assume t-student error innovations. The top panel shows the results for developed markets, while the bottom panel shows the results for their emerging counterparts. The last line in each panel shows the average value of the variables for each group.

As expected, average rate of return and unconditional volatility for emerging markets (0.041% and 1.867%) are higher than those for developed markets (0.017% and 1.448%). The best performing markets was Turkey, which achieved an average daily rate of return of 0.142%. In contrast, the worst performing market was Thailand, which registered a daily rate of return of -0.017%. In terms of unconditional volatility, 9 of 23 emerging markets recorded daily standard deviations greater than 2% (Argentina, Brazil, China, Hungary, Indonesia, Korea, Russia,Thailand and Turkey), while only one developed market (Finland) exceeded a standard deviation of 2%.

Almost all developed and emerging stock markets (the exceptions are Hong-Kong, Japan, Singapore, Sweden, Brazil, Chile, China, Colombia, Korea, Malaysia, Mexico, Philippines, Thailand and Turkey) exhibit negative skewness, indicating that the distributions of returns have long left tails. The highest skewness coefficients (in absolute value) correspond to stock markets (Malaysia and Ireland) which exhibit as well the highest excess of kurtosis (44.72 and 15.67, respectively). The lowest kurtosis coefficient is given by the stock market of Taiwan (5.03).

According to the Ljung-Box test statistic for serial correlation in the returns (*qstat*), all but four (Austria, New Zealand, Singapore and Sweden) countries show significant evidence at the 1% level of short-term linear dependence in the return series. On the other hand, the Ljung-Box test statistic for serial correlation in the absolute returns (*qstat2*) indicates the presence of nonlinear dependence and apparent conditional heteroskedasticity effects for all return series. In general, emerging market returns seem to have stronger linear dependence than developed market returns. By contrast, the nonlinear dependence behavior is more salient in developed market returns. This can be explained by the fact that the volatility in emerging markets is primarily driven by local factors (Bekaert and Harvey, 1997). The results of the Gaussian semi-parametric estimates of d suggest that there is strong evidence of long memory in the absolute returns for all the stock markets under study.

The average estimates of the persistence of shocks to volatility $\alpha + \beta + \gamma/2$ for developed and emerging markets are similar and very close to one (0.990 and 0.983, respectively). For developed markets the "good news" in the threshold GARCH model has an impact on conditional variance of $\alpha = 0.040$ while "bad news" has an impact of $\alpha + \gamma = 0.129$. In the case of emerging markets, "good news" has an impact of $\alpha = 0.091$ while "bad news" has an impact of $\alpha + \gamma = 0.168$. Hence, in both groups, the volatility tends to be higher in the presence of negative shocks.

3 The factor structure of the empirical properties

Standard statistical factor analysis describes the covariance relationships among observed variables in terms of a smaller number of unobserved latent variables, called factors. In statistical factor analysis for asset returns, the common factors are extracted from the covariances of asset returns (Tsay, 2005). An advantage of this technique over other types of factor models (e.g., fundamental and macroeconomic factor models) is the capability to identify the pervasive factors in asset returns without using any external data sources. As discussed in the introductory section, in our approach the factors are not extracted directly from the historical returns but from their empirical properties.

Let $y_1, y_2, ..., y_p$ be a set of p characteristics of the returns. The factor analysis model assumes the form

$$y_i = \theta_{i1}F_1 + \theta_{i2}F_2 + \cdots + \theta_{iq}F_q + u_i, \quad i = 1, ..., p, \tag{5}$$

where $F_1, F_2, ..., F_q$ are unobserved latent variables or common factors, θ_{ij} is the *factor loading* of the ith variable on the jth factor, and u_i is the error or *specific factor* of the ith variable. We assume that the specific errors are uncorrelated with each other and with the common factors $F_1, F_2, ..., F_q$. The variance of the ith variable is given by

$$\sigma_i^2 = h_i^2 + \psi_i, \tag{6}$$

where $h_i^2 = \theta_{i1}^2 + \cdots + \theta_{iq}^2$ is the ith *communality* and represents the portion of the variance of the ith variable shared with the other variables via the q common factors, and ψ_i is the remaining portion of the variance of the ith variable, called the *uniqueness* or *specific variance.*

We use the classic principal-component factor analysis method in the estimation of the factor loadings and communalities, which uses the square multiple correlations as estimates of the communalities to compute the factor loadings. This procedure drops factors with eigenvalues below 1 (Kaiser criterion). We then perform an orthogonal rotation of factors through the Varimax method to simplify the factor structure. The goal of this method is to obtain factors with a few large loadings and as many loadings close to zero as possible. Factor loadings greater than 0.5 (in absolute value) are considered significant for factor interpretation purposes. An acceptable factor solution occurred when all variables have a significant loading on a factor and no variable has more than one significant loading. The estimated rotated factor loadings are used to compute the factor scores of each individual observation, using the regression scoring method. Factor scores are standardized to have zero mean and unit variance.

3.1 Factor loadings

To investigate the structure of international stock market returns through its empirical properties we apply principal-component factor analysis to the 10 variables introduced in Section 2

($mean$, $stdev$, $skew$, $kurt$, $qstat$, $qstat2$, d, α, β and γ). In addition to examining the results given by daily returns, we also inspect the results given by weekly and monthly returns.

In order to identify clusters of markets and possible multivariate outliers, we compute scores for the first two factors derived from factor analysis. We consider factor scores having values greater than ± 2 as outliers. Since outliers can impact correlations strongly and change the factor structure in the solution, we investigate whether communalities and factor loadings change in the factor solution by omitting stock markets that are considered outliers. Because the results indeed suggest that outliers have some impact on the factor structure, the factor analysis solution without outliers is used for interpretation purposes. In the factor analysis based on daily returns, the markets of Morocco, Colombia, Malaysia, Turkey and Chile were classified as outliers. The markets of Russia, Colombia, Malaysia and Turkey were considered outliers in the analysis based on weekly returns, and the markets of Russia, Argentina, Malaysia and Turkey were so in the analysis of monthly returns. The factor loadings are then transformed through the Varimax rotation.

The two sets of unrotated and rotated loadings for daily weekly and monthly returns are given in Table 2. Irrespectively of the sampling frequency, the factor analysis retained four factors with an eigenvalue of 1 or greater. For instance, in the factor solution based on daily returns, the cumulative variance accounted by these four factors is 7.93, which is about 79% (7.93/10) of the total variance. The factor 1 in the unrotated solution accounts for 30% (3/10) of the total variance and 37.8% (3/7.93) of the common variance, the factor 2 accounts for 22.6% of the total variance and 28.5% of the common variance, the factor 3 accounts for 13.7% of the total variance and 17.3% of the common variance, and the factor 4 accounts for 13% of the total variance and 16.4% of the common variance. The communalities indicate the amount of variance that each variable shares with all other variables in the set. All variables have communality estimates greater than 0.5, and 7 of the 10 variables ($stdev$, $skew$, $qstat$, $qstat2$, α, β and d) have communality estimates greater than 0.8, which means that these variables are highly correlated with the retained factors.

Using the threshold of ± 0.5 for identifying significant loadings, we can see that all variables in the rotated solutions have a significant loading on a factor and no variable has significant cross-loadings on the other factors. Only the *mean* variable in the monthly returns based solution loads significantly on two factors (1 and 2). The pattern of factor loadings suggest the following relations. First, the presence of non-linear dependence is more salient in markets with stronger long-memory behavior. Second, the unconditional volatility is positively correlated with the mean return, which is simply a materialization of the basic risk-return tradeoff concept. Third, the presence of linear dependence is more prominent in markets with lower volatility. Finally, the leverage effect and skewness are positively related.

3.2 Factor scores

Figure 1 shows bi-dimensional plots of stock market scores given by the two factors that explain the largest proportion of the total variance. In order to allows us to better distinguish developed markets from their emerging counterparts, the latter are displayed in gray. The

Daily data

	Unrotated factors				Rotated factors				
Variable	F1	F2	F3	F4	F1	F2	F3	F4	Communality
mean	0.31	-0.50	-0.01	0.51	0.26	-0.10	0.71	-0.13	0.60
stdev	0.01	-0.49	0.36	0.67	-0.13	-0.06	0.89	0.13	0.83
skew	0.37	-0.06	0.84	-0.19	0.21	-0.06	0.13	0.91	0.89
kurt	0.30	0.61	0.32	0.31	0.10	0.73	0.04	0.34	0.66
qstat	0.88	0.02	-0.13	-0.32	0.92	0.01	-0.18	0.11	0.89
*qstat*2	-0.09	0.84	-0.26	0.23	-0.16	0.80	-0.33	-0.24	0.83
d	0.38	0.70	-0.02	0.46	0.22	0.89	0.04	0.00	0.84
α	0.94	-0.13	-0.23	0.01	0.96	0.06	0.15	-0.07	0.95
β	-0.93	0.02	0.02	0.11	-0.91	-0.09	-0.05	-0.17	0.87
γ	-0.15	0.43	0.53	-0.29	-0.25	0.19	-0.35	0.59	0.57
Eigenvalue	3.00	2.26	1.37	1.30	2.87	2.03	1.61	1.42	
Proportion	0.30	0.23	0.14	0.13	0.29	0.20	0.16	0.14	

Weekly data

	Unrotated factors				Rotated factors				
Variable	F1	F2	F3	F4	F1	F2	F3	F4	Communality
mean	-0.32	0.67	0.02	-0.16	-0.21	0.59	0.42	-0.14	0.58
stdev	-0.34	0.53	0.56	0.33	0.09	0.83	0.02	0.35	0.82
skew	-0.41	-0.06	0.04	0.86	-0.13	0.11	-0.03	0.94	0.91
kurt	0.76	0.25	0.02	-0.11	0.68	-0.12	0.27	-0.33	0.66
qstat	0.51	0.30	0.55	-0.18	0.66	0.35	-0.09	-0.34	0.68
*qstat*2	0.81	0.04	0.43	0.17	0.93	-0.02	-0.12	-0.06	0.88
d	0.88	0.09	0.06	0.28	0.87	-0.26	0.19	0.02	0.87
α	-0.13	0.81	-0.26	0.00	-0.10	0.42	0.75	-0.05	0.75
β	-0.33	-0.59	0.68	-0.16	-0.14	0.19	-0.94	-0.00	0.94
γ	0.68	-0.26	-0.43	0.23	0.44	-0.72	0.21	0.07	0.76
Eigenvalue	3.25	1.99	1.51	1.10	2.81	1.99	1.80	1.26	
Proportion	0.33	0.20	0.15	0.11	0.28	0.19	0.18	0.13	

Monthly data

	Unrotated factors				Rotated factors				
Variable	F1	F2	F3	F4	F1	F2	F3	F4	Communality
mean	-0.55	0.51	0.28	-0.25	-0.54	0.56	0.26	0.18	0.70
stdev	-0.43	0.40	0.57	0.45	0.05	0.93	-0.02	-0.03	0.87
skew	-0.66	-0.25	-0.15	0.55	-0.15	0.36	-0.82	-0.09	0.83
kurt	0.37	0.38	0.67	-0.37	0.12	0.23	0.88	-0.13	0.86
qstat	0.72	0.19	0.20	0.07	0.61	-0.11	0.46	0.06	0.61
*qstat*2	0.65	0.08	0.30	0.60	0.92	0.16	0.11	-0.05	0.88
d	0.83	0.15	-0.13	0.34	0.83	-0.27	0.17	0.26	0.85
α	0.00	0.75	-0.57	0.21	0.06	0.10	-0.09	0.95	0.93
β	-0.48	-0.41	0.53	0.24	-0.13	0.46	-0.27	-0.65	0.73
γ	0.65	-0.57	0.11	-0.09	0.44	-0.55	0.16	-0.49	0.76
Eigenvalue	3.35	1.74	1.64	1.30	2.44	2.00	1.88	1.70	
Proportion	0.33	0.17	0.16	0.13	0.24	0.20	0.19	0.17	

Table 2: Factor analysis for the empirical properties of international stock market returns.

plot in the top of Figure 1 shows the results for daily returns. This plot exhibits two rather distinct clusters. We can identify a cluster containing most developed markets at negative values of factor 1, and a cluster containing most emerging markets at positive values of factor 1. Clearly, this analysis reveals that the factor structure of the empirical properties of stock returns differs substantially between developed and emerging markets. Nevertheless, it is interesting to note that five emerging markets (Israel, Korea, Mexico, Poland and Taiwan) present scores on factor 1 in the range of the cluster of developed markets, but larger negative scores on factor 2. Also noteworthy is that the markets of Israel and Taiwan have larger negative scores on factor 1 than most developed markets. This is no surprise since these markets have developed past the emerging market phase, despite the classification as "emerging" by MSCI.

The plots in the middle and bottom of Figure 1 show the results for weekly and monthly returns, respectively. Differences between developed and emerging markets are also perceptible for lower sampling frequencies. However, these differences are not so pronounced as those observed when using daily data. For small sample sizes the accuracy of some estimators may be questionable. Nevertheless, for lower sampling frequencies the most developed markets tend to exhibit larger positive scores on factor 1 and larger negative scores on factor 2.

4 Conclusions

This study examined the behavior of international stock market returns in terms of their empirical properties, such as the distributional properties, serial dependence, long-memory and conditional volatility. A factor analysis approach was employed to identify the underlying dimensions of the returns. This analysis reveals the existence of meaningful factors when these are estimated from the empirical properties of international stock market returns. Also, the pattern of factor loadings indicated that: (i) the presence of non-linear dependence is more important in markets with stronger long-memory; (ii) the unconditional variance is positively correlated with the mean return; (iii) the presence of linear dependence is more salient in markets with lower volatility; and (iv) the leverage effect and skewness are positively related. The estimated factor loadings were then used to generate scoring coefficients for each stock market. It was shown that the scores given by the factors that explain the largest proportion of the variance discriminate remarkably well international stock markets according to size and level of development.

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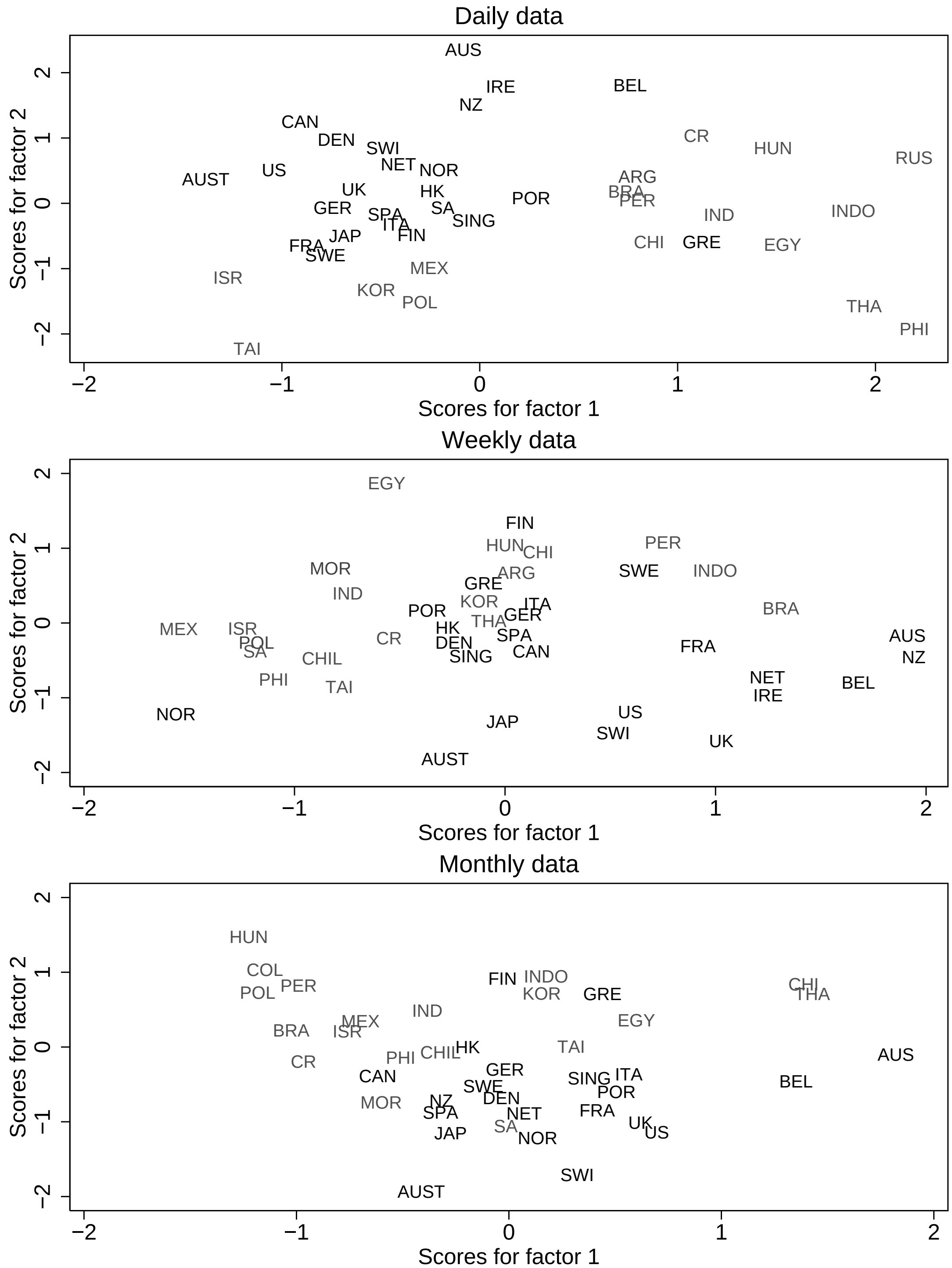

Figure 1: Score plots of the two principal factors for stock markets returns.

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