INTERNATIONAL JOURNAL OF BUSINESS, 9(1), 2004 ISSN:1083-4346

Why Does Stock Market Volatility Differ across Countries? Evidence from Thirty Seven International Markets

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ABSTRACT

There are substantial differences in stock market volatility across countries. This paper asks why market volatility differs across countries. Using Datastream Country Indexes covering thirty seven international markets, this paper finds that the education level of investors plays a significant role in explaining cross-country market volatility differences. In addition, there is some evidence indicating that market industry concentration, the relative size of the stock market, and the number of firms listed may also be of significant explanatory power to cross-sectional market volatility differences. These findings can help predict international market volatility.

JEL: *G15, E44*

Keywords: *Stock market volatility; International stock markets; Determinants of market volatility*

I. INTRODUCTION

Dramatic volatility differences across international stock markets have been observed (see, for instance, Roll (1992), Harvey (1995a), Bekaert and Harvey (1997), and Aggarwal, Inclan, and Leal (1999)). However, the reason why market volatility differs across countries remains unclear. Cohen, et al. (1976), using data from three markets, the U.S., the U.K. and Japan, provide evidence that differences in returns variance across the exchanges are largely explained by differences in market thinness and share turnover. Grinold, Rudd, and Stefek (1989) find that both industry and country explain part of the typical stock's return behavior. Roll (1992) compares 24 equity price indexes and claims that countries' industrial structure explains approximately 40% of volatility differences among markets. However, Heston and Rouwenhorst (1994) and Griffin and Karolyi (1998) find that market industry composition can explain little of the variation in country index returns.

The purpose of this paper is to provide some new insights into the question of why market volatility differs across countries. This question is important because, by answering this question, we may be able to identify critical factors that drive market volatility, which is a key element of modern finance theory. To investigate this question, we use a new, large database, Datastream Country Indexes. This database includes thirty seven countries, covers the period from 1973 through 2000, and contains observations from both developed and emerging markets in a nearly balanced manner. Using such a large database, we hope that the sample size limitation typically shared by previous studies can be avoided and, consequently, sample selection bias can be nearly eliminated.

Our major findings are as follows. The average education level of investors in a market, proxied by school life expectancy in a country, is significantly and negatively related to market volatility across countries. We interpret this result as evidence supporting the notion that the collective characteristics of investors in a market play a significant role in shaping market volatility. Market industry concentration, proxied by a Herfindahl variable, may also be a significant factor in explaining volatility differences across markets. Specifically, we find a significant, positive relationship between market industry concentration and market volatility. This finding is consistent with that of Roll (1992). The relative market size, which is measured by the ratio of total market capitalization over gross domestic production (GDP) in a country, is negatively associated with cross-sectional market volatility. Smaller stock markets are more volatile. This result confirms Bekaert and Harvey's (1997) conjecture. A weak, negative relationship between the number of listed firms and market volatility is also found.

The remainder of the paper is separated into five sections. Section II describes the sample. Section III provides details about how we measure market volatility. Section IV describes potential factors that may affect market volatility. Section V contains empirical results. Section VI provides a summary and a conclusion.

Table 1
Univariate statistics for weekly stock market index returns in thirty seven countries

This table contains univariate statistics for Datastream weekly stock market index returns in thirty-seven markets. The time period covered is from the first trading week of the starting year through May 17, 2000. Ljung-Box Q-statistics with 16 lags are used to test serial correlation of weekly stock returns. *, **, and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Country	Starting Year	Mean	STD[a]	Skewness	Kurtosis	Ljung-Box Q(16)
Developed						
Australia	1973	0.0011	0.032	-1.14***	13.69***	36.8***
Austria	1973	0.0014	0.027	0.41***	5.52***	62.3***
Belgium	1973	0.0014	0.024	-0.16***	1.60***	32.5***
Canada	1973	0.0013	0.022	-0.46***	3.35**	37.7***
Denmark	1973	0.0021	0.027	-0.01	6.43***	15.8
Finland	1988	0.0033	0.037	-0.16	2.28***	26.6**
France	1973	0.0020	0.029	-0.49***	2.38***	37.5***
Germany	1973	0.0018	0.024	-0.27***	1.53***	28.9**
Hong Kong	1973	0.0019	0.046	-0.70***	5.43***	74.1***
Ireland	1973	0.0018	0.031	-0.14***	4.27***	45.1***
Italy	1973	0.0015	0.035	-0.32***	2.09***	55.4***
Japan	1973	0.0019	0.028	0.12**	1.94***	28.2**
Netherlands	1973	0.0021	0.022	-0.18***	2.55***	11.3
New Zealand	1988	0.0003	0.029	0.08	2.44***	26.6**
Norway	1973	0.0015	0.034	-0.23***	2.16***	33.3***
Singapore	1973	0.0010	0.036	-1.11***	15.32***	74.4***
Spain	1986	0.0016	0.029	-0.45***	2.63***	28.6**
Sweden	1980	0.0031	0.032	-0.26***	1.64***	16.0
Switzerland	1973	0.0021	0.023	-0.42***	2.60***	27.3**
UK	1973	0.0017	0.027	-0.04	5.92***	33.2***
US	1973	0.0018	0.021	-0.59***	3.32**	20.6
Emerging						
Argentina	1987	0.0046	0.096	-1.21***	23.40***	39.4***
Brazil	1994	0.0008	0.055	-0.77***	4.85***	34.2***
Chile	1988	0.0030	0.032	0.10	1.76***	36.6***
China	1990	0.0054	0.073	1.16***	11.13***	17.3
Greece	1988	0.0033	0.046	0.04	1.43***	24.6*
Indonesia	1989	-0.0028	0.063	-0.55***	7.33***	33.4***
Korea	1987	0.0006	0.051	-0.59***	7.35***	55.3***
Malaysia	1982	0.0017	0.049	-1.27***	13.81***	26.9**
Mexico	1988	0.0042	0.051	0.27***	5.54***	24.8*
Philippine	1987	0.0016	0.044	-0.30***	3.11	46.5***
Poland	1994	-0.0019	0.059	-0.24	2.25***	23.3
Portugal	1990	0.0007	0.026	0.03	1.03***	9.0
South Africa	1973	0.0011	0.037	-0.44***	2.24***	32.1***
Taiwan	1987	0.0020	0.055	-0.20**	2.50***	26.1*
Thailand	1987	0.0011	0.052	-0.07	2.17***	32.5***
Turkey	1988	0.0021	0.073	-0.10	1.55***	24.3*
Summary[b]						
Developed		0.0017	0.029	-0.31	4.24	
Emerging		0.0017	0.054	-0.26	5.72	
World	1973	0.0017	0.018	-0.52***	3.30**	33.7***

[a] STD = the standard deviation of weekly returns in the time period covered.
[b] Cross-sectional means are provided for Developed and Emerging markets respectively. All variables for the World are obtained using the Datastream world index.

II. SAMPLE DESCRIPTION

Weekly equity price indexes in U.S. dollar terms for thirty seven countries are extracted from Datastream. Datastream Country Indexes are computed and maintained by Datastream itself. We choose to use Datastream country indexes for two reasons. First, Datastream country indexes include more countries (thirty seven) and cover a longer period of time (17 Datastream indexes date back as far as 1973) than any other common country indexes. Second, Datastream country indexes, accounting for over 90% of the total market capitalization in each country included, are better than any other popular world indexes in terms of coverage.[1] Given their high level of tracking, Datastream country indexes could be more representative of the market behavior in various countries than any other commonly used indexes and thus provide an accurate and meaningful reflection of prevailing market conditions for each country. Return indexes are approximated by taking the logarithmic difference of the price indexes.

The sample period covered in this study is from the first week of the Datastream index-starting year through May 17, 2000 for each country. Table 1 provides the sample period for each market and the univariate statistics for weekly (Wednesday to Wednesday) market index returns. The statistics – mean returns, standard deviations, skewness, kurtosis, and the Ljung-Box Q statistics with 16 lags are reported. There are obvious differences in mean weekly returns across the countries. The highest mean weekly returns are in China, at 0.54%, and the lowest are in Indonesia, at –0.28%. However, the mean return for the emerging markets is almost the same as that for the developed markets. Twenty five of 37 markets have significant negative skewness and 4 have positive skewness. Thirty seven of the return series have fat tails with the exception of Philippine, as indicated by the significant kurtosis. Nonnormality in the data is also revealed by the coefficients of skewness and kurtosis. The Ljung-Box Q (16) statistics indicate significant serial correlations in 30 out of the 37 series.

III. VOLATILITY MEASUREMENT

GARCH models have been the workhorse for estimating conditional volatility since they were first introduced by Bollerslev (1986). However, conventional GARCH models are unable to capture the asymmetric effect of negative or positive returns on volatility. This effect, discovered by Black (1976), occurs when an unexpected drop in price increases volatility more than an unexpected increase in price of similar magnitude. The existence of this asymmetric effect implies that a symmetry specification on the conditional variance function as in a conventional GARCH model is theoretically inappropriate. To address this issue, Nelson (1990) proposes the following EGARCH model:

$$
\begin{aligned}
&R_t = \mu + \varepsilon_t \\
&\varepsilon_t = \sqrt{h_t}\, e_t \\
&e_t \sim N(0,1) \\
&\mathrm{Log}(h_t) = \omega + \alpha_1 \mathrm{Log}(h_{t-1}) + \alpha_2 \frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} + \alpha_3 \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - \sqrt{\frac{2}{\pi}} \right]
\end{aligned}
\tag{1}
$$

where R_t is the market return at week t and h_t is the conditional variance of return at week t. Apparently, this EGARCH model is asymmetric: positive return shocks generate less volatility than negative return shocks (all else being equal), since the coefficient of $\varepsilon_{t-1}/\sqrt{h_{t-1}}$ is typically negative.[2] Indeed, Engle and Ng (1993) find evidence that the EGARCH model is better than other GARCH models in modeling conditional volatility.

In this paper, we apply the above EGARCH model to each country index return series to obtain conditional variance estimates. The volatility series is computed by taking the positive square root of the estimated conditional variance series.[3] The annualized EGARCH volatility estimates are then computed as follows (similar to Schwert (1997)):

$$AVOL_{ij} = \overline{WVOL_{ij}} \times \sqrt{N_{ij}} \tag{2}$$

where $AVOL_{ij}$ is the annualized market volatility in year i and country j, $\overline{WVOL_{ij}}$ is the mean weekly conditional volatility in year i and country j, and N_{ij} is the number of weekly returns in year i and country j.

It is necessary to point out that $AVOL_{ij}$ is by no means a true measure of annual volatility since we are forced to assume independence of weekly returns when computing it as in Eq. (2). However, Eq. (2) does provide us with an adequate measure of annual volatility level that is comparable across markets. To see this, notice that we can rewrite Eq. (2) as $AVOL_{ij} = (\sum_{t=1}^{N} WVOL_{ij}) / \sqrt{N}$, where $WVOL_{ij}$ is weekly conditional volatility in week t and country j. Since the number of weekly returns in a year, N, is almost the same across markets and over time, AVOL actually reflects the sum of weekly volatility values in a year. It is clear that, although AVOL is not a true measure of annual volatility, it does allow us to compare annual volatility levels across markets.

Table 2 summarizes market volatility in our sample. There are substantial volatility differences across markets. On average, the most volatile market is Argentina, with an average annualized volatility of 0.56. The least volatile market is the U.S., Canada, and the Netherlands, all of which have an average annualized volatility of 0.15. Developed markets are on average less volatile than emerging markets. These results are consistent with those obtained by using other country indexes (see, for example, Harvey (1995b)).

Table 2
Annualized market volatility in thirty seven countries

This table reports each market's annualized volatility in 1973, 1988, 1999 and the average for the period from the index-starting year through 1999. The index-starting year for each market is shown in Table 1. "." indicates that the corresponding data are not available.

	1973	1988	1999	Average
Developed				
Australia	0.22	0.30	0.20	0.22
Austria	0.19	0.15	0.17	0.17
Belgium	0.18	0.19	0.20	0.17
Canada	0.15	0.16	0.16	0.15
Denmark	0.19	0.19	0.19	0.19
Finland	.	0.17	0.29	0.25
France	0.20	0.21	0.20	0.20
Germany	0.18	0.18	0.21	0.16
Hong Kong	0.56	0.26	0.28	0.30
Ireland	0.18	0.22	0.23	0.21
Italy	0.26	0.22	0.23	0.25
Japan	0.23	0.17	0.22	0.19
Netherlands	0.17	0.13	0.17	0.15
New Zealand	.	0.24	0.21	0.20
Norway	.	0.25	0.21	0.24
Singapore	0.44	0.27	0.27	0.25
Spain	.	0.18	0.22	0.20
Sweden	.	0.20	0.23	0.23
Switzerland	0.17	0.15	0.17	0.16
UK	0.17	0.17	0.19	0.19
US	0.17	0.17	0.16	0.15
Emerging				
Argentina	.	0.72	0.39	0.56
Brazil	.	.	0.46	0.35
Chile	.	.	0.23	0.22
China	.	.	0.49	0.50
Greece	.	0.28	0.39	0.32
Indonesia	.	.	0.61	0.36
Korea	.	0.28	0.44	0.32
Malaysia	.	0.30	0.40	0.31
Mexico	.	0.43	0.32	0.33

Table 2 (continued)

	1973	1988	1999	Average
Philippine	.	0.25	0.31	0.29
Poland	.	.	0.33	0.39
Portugal	.	.	0.22	0.18
South Africa	0.26	0.26	0.26	0.26
Taiwan	.	0.46	0.29	0.36
Thailand	.	0.30	0.51	0.35
Turkey	.	0.36	0.59	0.51
Summary[a]				
Developed	0.23	0.20	0.21	0.20
Emerging	0.26	0.37	0.39	0.35
World	0.14	0.13	0.15	0.12

[a] ross-sectional means are provided for Developed and Emerging markets respectively. All variables for the World are obtained using the Datastream world index.

IV. FACTORS AFFECTING MARKET VOLATILITY[4]

A. Market Industry Concentration

Modern portfolio theory predicts a significant relationship between market industry concentration and market volatility. High industry concentration in a market means less diversification. Therefore, high industry concentration would lead to high market volatility. However, previous studies find conflicting results with regard to the role of market industry structure in explaining volatility (Roll (1992), Heston and Rouwenhorst (1994), and Griffin and Karolyi (1998)).

Following Roll (1992), we use a Herfindahl variable to proxy for market industry concentration in each market. Specifically, at each week, the market industry concentration in country i is computed as

$$IND_i = \sum_{j=1}^{n} \left(\frac{MVIND_{ij}}{CAP_i} \right)^2 \tag{3}$$

where IND_i is the industry concentration measure for country i, $MVIND_{ij}$ is the market value of industry *j* (j = 1, 2, . . . , n) in country *i,* and CAP_i is country *i*'s total market capitalization. The yearly market industry concentration is then approximated by the mean of weekly industry concentration values in a year.

Our market industry data are obtained from Datastream. Datastream groups all stocks in a market into ten major industry sectors (therefore, n = 10 in Eq. (3) for each market). These industry sectors are: Resources; Financial Industries; Basic Industries; General Industries; Cyclical Consumption Goods; Non Cyclical Consumption Goods; Cyclical Services; Non Cyclical Services; Utilities; and Information Technology.

It should be clear that market industry concentration, *IND*, goes from 0.1 (all listed firms are equally distributed into 10 industries) to 1 (all listed firms are concentrated on any of the 10 industries). The bigger the market industry concentration, the more concentrated the listed firms. As summarized in Table 3, market industry concentration differs substantially across countries. The cross-country average industry concentration is 0.2392. Among the thirty-seven countries, the U.S. has the smallest industry concentration, which is 0.11 and South Africa, the highest, 0.47. Moreover, industry concentration in the emerging markets is on average slightly higher than that in developed markets.

Table 3
Factors affecting market volatility in thirty seven countries

Country	Industry Concentration[a]	Education[b]	CAP/GDP (%)[c]	Nfirm[d]
Developed				
Australia	0.25	14.6	73.04	1156
Austria	0.26	14.4	12.52	101
Belgium	0.19	15.4	39.55	165
Canada	0.15	16.7	58.9	1177
Denmark	0.23	14.3	34.03	252
Finland	0.18	15.5	30.96	73
France	0.13	14.8	33.63	598
Germany	0.19	15.3	25.65	565
Hong Kong	0.29	.	195.61	429
Ireland	0.27	13.2	26.27	80
Italy	0.33	.	17.58	226
Japan	0.14	13.3	88.12	2163
Netherlands	0.23	15.3	70.64	239
New Zealand	0.18	15.2	51.88	180
Norway	0.28	14.6	25.9	135
Singapore	0.30	.	137.4	190
Spain	0.22	.	31.51	391
Sweden	0.27	13.8	65.26	210
Switzerland	0.34	10.9	112.19	200

Table 3 (continued)

Country	Industry Concentration[a]	Education[b]	CAP/GDP (%)[c]	Nfirm[d]
UK	0.15	15.3	113.77	1954
US	0.11	15.8	83.8	7339
Emerging				
Argentina	0.31	.	10.47	166
Brazil	0.19	10.6	18.27	562
Chile	0.21	12.1	80.94	250
China	0.22	.	9.31	310
Greece	0.34	13.2	13.54	166
Indonesia	0.22	9.8	15.76	167
Korea	0.18	13.6	.	.
Malaysia	0.14	.	184.95	421
Mexico	0.26	10.8	28.32	198
Philippine	0.27	11.0	47.67	178
Poland	0.24	12.6	3.7	55
Portugal	0.30	14.1	18.15	176
South Africa	0.47	13.7	156.51	680
Taiwan	0.29	.	.	.
Thailand	0.28	.	51.63	315
Turkey	0.16	8.8	13.52	151
Summary[e]				
Developed	0.21	14.6	63.25	849
Emerging	0.24	11.8	44.38	261
World	0.11	.	.	.

[a] Industry Concentration = the time-series mean of weekly industry concentration in each market. The industry concentration of each market is measured by a Herfindahl variable. For each week, we compute the Herfindahl industry concentration measure as follows:

$$\mathrm{IND}_i = \sum_{j=1}^{10}\left(\frac{\mathrm{MVIND}_{ij}}{\mathrm{CAP}_i}\right)^2$$

where IND_i is the industry concentration measure for countryi, MVIND_{ij} is the market value of industry j in country i, and CAP_i is country i's total market capitalization. We use Datastream market industry data. Datastream groups all stocks listed in a market into 10 major industry sectors. The time span covered for each market is the same as indicated in Table 1.

[b] Education = the average education level of investors, which is proxied by school life expectancy, in each country from 1988 through 1996. The education data are obtained from the United Nations Organization for Education, Science and Culture (UNESCO).

[c] CAP/GDP (%) = the time-series mean of the yearly relative size of the equity market in each country from 1988 to 1997. The relative market size in a year is computed as follows:

$$CAP / GDP = 100 \times \frac{CAP}{GDP}$$

where *CAP* is the total market capitalization of all listed firms in a market and *GDP* is the gross domestic production (GDP) of that particular country. Both *CAP* and *GDP* are from the World Development Indicator database of the World Bank.

[d] Nfirm = the time-series mean of the yearly number of listed domestic firms in each market from 1988 (or the starting year of the Datastream index for a particular country if its start year is after 1988) to 1997. These data are from the World Development Indicator database of the World Bank.
[e] Cross-sectional means of the corresponding variables are provided here for Developed and Emerging markets, respectively. All variables of the World are solely for the Datastream world index.
. Indicates that the corresponding data are not available.

B. The Average Education Level of Investors

Investors typically exhibit a strong "home bias."[5] Given the existence of this bias, local investors' collective behavior could be decisive in shaping stock market movements in a country. Thus, the collective characteristics of investors that may influence their behavior should not be neglected when one examines stock market fluctuations. We choose the average education level of investors, which itself is represented by the school life expectancy in a country,[6] as a proxy for the collective characteristics of all investors in a market. Since better-educated people may have better cognitive and analytical capability and thus behave more rationally, we therefore expect that the average education level of investors is negatively related to market volatility.

The education data are obtained from the United Nations Organization for Education, Science and Culture (UNESCO). International education data on school life expectancy are available from 1988 to 1996. Table 3 presents the average education level of investors over the period for each market. There are enormous differences across countries in the average education level of investors. The sample average of this level is 13.6. Canada and the U.S. have the highest level, 16.7 and 15.8 years respectively, when averaged over the 9 years. By contrast, Turkey and Indonesia have the lowest, 8.8 and 9.8 years, respectively. People in developed markets are on average better educated than are those in emerging markets.

C. The Relative Size of the Equity Market

The relative size of the equity market in a country is defined as:

$$\mathrm{CAP/GDP} = 100 \times \frac{\mathrm{CAP}}{\mathrm{GDP}} \tag{4}$$

where CAP is the total market capitalization of all listed firms in a market and GDP is the gross domestic production (GDP). Harvey (1995a) argues that, in a larger market, noise trading is probably offset more completely by one another and thus is less influential. Therefore, market size would be related to market volatility. The larger the market size, the more stable the market could be.

Annual data for CAP/GDP from 1988 to 1997 are also obtained from the World Bank. Table 3 shows the average relative equity market size of each country through time. On average, developed markets are larger than emerging markets. There are 6 markets, Hong Kong, Malaysia, South Africa, Singapore, the U.K., and Switzerland that have a CAP/GDP ratio over 100%. This means that, in these markets, the total market capitalization is greater than GDP. The biggest (relative) markets are Hong Kong (195.61) and Malaysia (184.95), while Poland (3.7) and China (9.31) are the smallest.

D. The Number of Listed Firms

On the one hand, the total number of listed firms may be positively related to market industry concentration. It might be the case that the more firms listed, the more diversified the market. On the other hand, it could also be true that the more firms listed, the larger the relative market size. In either case, the number of listed firms could be negatively related to market volatility.

We use the total number of listed domestic firms to proxy for the total number of listed firms in a market. This practice should be acceptable because domestic firms usually dominate the stock market in every country. Data for the number of listed domestic firms are from the World Development Indicator database of the World Bank. Yearly data are available for every country except Taiwan from 1988 to 1997. Table 3 contains the average number of listed domestic firms over 10 years from 1988 through 1997. As expected, developed markets, on average, have more firms listed than emerging markets (849 versus 261). The U.S., with an average of 7339 domestic firms listed from 1988 to 1997, has more firms listed that any other country. By contrast, Poland, which has the smallest number of listed firms, has only 55 listed domestic firms on average.

V. EMPIRICAL RESULTS

A. Univariate Regressions

The stand-alone explanatory power of each explanatory variable on the cross-sectional difference of market volatility is examined by estimating the following univariate cross-sectional regression model as employed by Roll (1992):

$$\text{Log}(\text{ANNVOL}_t) = \alpha + \beta \times \text{EXPVAR}_t + \varepsilon_t \tag{5}$$

where ANNVOL_t is the annualized market volatility estimated in Section III for all countries in year t, EXPVAR_t is an explanatory variable for all countries in year t, and ε_t is assumed to be a white noise. In turn, we cross-sectionally regress the logarithmic value of annualized volatility on each of the four explanatory variables year by year. The four explanatory variables are those discussed in Section IV. All variables are expressed in their annual values. We use the raw value of market industry concentration, instead of its logarithmic value, to keep in line with Roll (1992). For each year during which an explanatory variable is available, a cross-country regression is performed.

Table 4

Univariate regressions of log market volatility on various explanatory variables

OLS regressions of log market volatility on each of the explanatory variables with an intercept in the model are performed year by year whenever the relevant data are available. For example, market volatility and market industry concentration measures are both available from 1973 to 1999 and we then regress log market volatility on market industry concentration 27 times year by year from 1973 to 1999. Log market volatility is obtained by taking the log value of 100 times the annualized volatility. Industry Concentration = the Herfindahl market industry concentration measure; LEDU = the log value of the average education level of investors; LCAPGDP = the log value of the relative market size measured by 100 times the ratio of total market capitalization to the GDP; LNFIRM = the log value of the number of listed domestic firms. Fisher's (1950) method, i.e., Fisher's χ^2, is employed to aggregate statistical tests in year-by-year independent regressions:

$$-\sum_{i=1}^{n} 2\,\mathrm{Log}\ (P_i) \sim \chi^2_{(2n)}$$

where P_i is the probability for the i^{th} test that the specified null hypothesis is true and n is the total number of independent tests. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

	Industry Concentration	LEDU	LCAPGDP	LNFIRM
Period of Time	73-99	88-96	88-97	88-97
Number of Regressions	27	9	10	10
Mean Coefficient	1.09	-1.299	-0.187	-0.128
(Standard Deviation of Coefficients)	(0.457)	(0.158)	(0.059)	(0.053)
Percentage of Sig. t-stats	74%	89%	100%	70%
Percentage of Neg. t-stats	0.00%	100%	100%	100%
Fisher's χ^2	199.6***	42.1***	44.9***	29.2*
Range of Degrees of Freedom	26-36	14-28	25-34	28-35
Mean R^2	0.216	0.36	0.23	0.141

Our estimation technique is ordinary least squares using the standard White (1980) correction for conditional heteroskedasticity. We assume that yearly regression estimation errors are independent over time. Under this assumption, Fisher's (1950) method can be utilized to aggregate statistical tests in year-by-year regressions. Under Fisher's method, if *n* independent tests yield p-values with respect to the probability that a hypothesis is true; the *n* p-values can be used to create a statistic, T, that is distributed as a chi-square with $(2 \times n)$ degrees of freedom:

$$T = -\sum_{i=1}^{n} 2\mathrm{Log}(P_i) \sim \chi^2_{(2n)} \qquad (6)$$

where P_i is the probability for the i^{th} test that the specified null hypothesis is true.

Table 4 summarizes the results of regressions. We find a significant cross-country relation between market volatility and market industry concentration. First of all, in most years from 1973 to 1999, industry concentration is significantly related to market volatility. Second, the mean coefficient of industry concentration in the regressions over the 27 years from 1973 to 1999 is significantly different from zero. This can be indicated by the ratio of the mean coefficient to the standard deviation of the coefficients. Third, Fisher's chi-square test rejects the null hypothesis that the individual tests are jointly insignificant. Fourth, all significant coefficients of industry concentration are positive. This is indicative of the positive relationship between industry concentration and market volatility: the higher the market industry concentration, the more volatile the market. Finally, the explanatory power of industry concentration to market volatility is not trivial. It is about 21% in our sample. Although this figure is less than that documented by Roll (1992), which is over 40%, it is still substantial. To summarize, we find a statistically significant, positive cross-sectional relationship between market industry concentration and market volatility. The market industry concentration alone can explain about 21% variation in cross-sectional market volatility. These findings are consistent with those of Roll (1992).

Similarly, we find a significant, negative relation between the average education level of investors and market volatility. The education level of investors itself can explain 36% variation in cross-sectional market volatility. This result implies that the better educated the investors in the market, the less volatile the market. We interpret this result as evidence supporting the idea that the collective characteristics of investors are a significant factor in shaping market volatility. The relative market size is negatively related to market volatility. On average, the relative market size can explain 23% of the cross-sectional variation of market volatility. This finding confirms Bekaert and Harvey's (1997) conjecture. We also find a significant and negative relationship between the number of firms listed and market volatility, but the relation is relatively weak. The explanatory power of the number of firms is dropped substantially to 14.1%.

B. Multiple Regressions

Simple regressions above provide us with stand-alone explanatory powers of individual variables. However, this approach is limited since it ignores the possible effects of other factors. To control for the effects of other factors while examining the relationship between market volatility and any of its explanatory variables, we perform multiple regressions. We run cross-sectional, multiple regressions year by year from 1989 to 1995, during which most of our data are available. The dependent variable is log market volatility, which is the log value of 100 times the annualized EGARCH volatility. The explanatory variables are the four factors affecting market volatility as discussed in Section III. Our estimation technique is ordinary least squares (OLS) using the standard White (1980) correction for conditional heteroskedasticity.

Table 5 reports the results of multiple regressions. As shown in the table, we find that the average education level of investors is the most important factor affecting cross-sectional variation of market volatility. It seems that this factor dominates others in explaining market volatility: even when other factors are controlled for, it remains significant and carries the expected sign. However, evidence regarding other explanatory variables is not clear. It is also worth noting that all models are significant and produce a substantial R^2. This further justifies our consideration of the four factors affecting market volatility.

Table 5
Multiple regressions of log market volatility on various explanatory variables

All models include an intercept. We run multiple regressions year by year from 1989 to 1995. The dependent variable is log market volatility, which is the log value of 100 times the annualized volatility. Reported in this table include the estimated coefficients of explanatory variables and robust t-statistics (in parentheses) for these coefficients. Industry Concentration = the Herfindahl market industry concentration measure; LEDU = the log value of the average education level of investors; LCAPGDP = the log value of the relative market size measured by 100 times the ratio of total market capitalization to the GDP; LNFIRM = the log value of the number of listed domestic firms; df = the degree of freedom of the model. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Year	Industry Concentration	LEDU	LCAPGDP	LNFIRM	df	F-stat	Adj. R^2
89	0.192	-0.746**	-0.219***	-0.017	15	14.98***	0.789
	(0.44)	(-2.49)	(-3.52)	(-0.35)			
90	1.945**	-1.687***	0.261	-0.051	14	6.15***	0.595
	(2.23)	(-3.29)	(1.31)	(-0.60)			
91	0.265	-0.778*	-0.110	-0.068	17	4.53**	0.454
	(0.37)	(-1.99)	(-1.18)	(-0.77)			
92	-1.273**	-0.863***	-0.132**	-0.099**	20	8.18***	0.590
	(-2.37)	(-3.02)	(-1.94)	(-1.89)			
93	-1.622***	-1.529***	-0.216**	-0.083	19	8.68***	0.618
	(-2.58)	(-4.13)	(-2.23)	(-1.36)			
94	-1.192	-1.537***	0.001	-0.087	24	5.52***	0.430
	(-1.51)	(-4.10)	(0.01)	(-1.37)			
95	-0.802	-1.895***	-0.086	-0.059	19	3.79**	0.370
	(-0.55)	(-2.67)	(-0.76)	(-0.79)			
Mean	-0.355	-1.291	-0.072	-0.066	18	7.40	0.549

C. Pooled Time-series Cross-section Analysis

Our simple and multiple regressions above present some features desirable for the analysis. For example, these regression models allow for different relationships between the dependent variable and explanatory variables in different years and the results are easy to interpret. However, these techniques are not unproblematic. On the one hand, these regressions typically have limited degrees of freedom. This limitation may lead the reader to question the reliability of our results, especially for the multiple regressions. On the other hand, combining developed and emerging countries may also be problematic. These two groups may be too heterogeneous to allow for meaningful cross-country comparison of stock market volatility. One way to mitigate these potential problems is to perform time-series cross-section analysis on the pooled data. Pooling the time-series cross-section data can substantially increase degrees of freedom in estimation and, consequently, make it feasible to separate developed and emerging countries in the analysis. An additional advantage of pooled data set over a cross section is that it allows for much greater flexibility in modeling cross-sectional differences.

We first pool cross-sectional data of all thirty-seven countries for seven years from 1989 through 1995, as used in our multiple regressions. We then divide the pooled data into two subsets, one including developed countries and the other containing emerging markets. We consider two competing models that may be appropriate for the pooled data:[7]

$$Y_{it} = \alpha_i + \beta' X_{it} + \varepsilon_{it} \tag{7}$$

and

$$Y_{it} = \alpha + \beta' X_{it} + u_i + \varepsilon_{it} \tag{8}$$

respectively, where Y_{it} is log market volatility in country i and year t, α_i is a country specific constant, β is a 4×1 vector of free parameters, X_{it} is a 4×1 vector of explanatory variables as used in Section V.B, α is constant, μ_I is the random disturbance characterizing country *i* and is constant over time, ε_{it} is an error term.

Model (7) is known as the fixed effects model because it assumes that cross-sectional differences can be captured in the constant term. The fixed effects model is a reasonable approach if we are confident that the cross sectional differences can be viewed as parametric shifts of the regression function. Model (8) is referred to as the random effects model since it views individual specific constant terms as randomly distributed across cross-sectional units. The random effects model would be appropriate if we believe that sampled cross-sectional units were drawn from a large population. These two models are not compatible in the sense that one of them cannot give consistent or efficient coefficient estimators if the other is true. Since both models are possible in our setting, there is the need to decide on which model to use for our pooled data.

We use Hausman's (1978) specification test to test for fixed or random effects. Under the null hypothesis that there are random effects, Hausman's test statistic, w, is asymptotically distributed as χ^2 with k degrees of freedom, where k is the number of regressors in the model. For the entire pooled data set, w is 4.20. For the two subsamples, w is 3.09 for the emerging subset and 5.13 for the developed subset respectively. Since none of the Hausman's test statistics is statistically significant at any conventional significance levels, we cannot reject the null that there are random effects. Therefore, we choose the random effects model as our pooling time-series cross-section technique.

Table 6 presents estimation results of the random effects model. Using pooled data including all countries, we find that the average education level of investors is highly significant in the model. This confirms our finding in cross-sectional multiple regressions that the average education level of investors is the most important factor affecting cross-sectional variation of market volatility. Using the subsample containing only developed markets, we are still able to show that the average education level of investors is a significant explanatory variable. This indicates that our regression results are not produced by the heterogeneity between developed and emerging markets. We are not able to find any significant variable in the emerging sample. However, this may be simply because the number of observations in the emerging sample is not large enough to allow for precise estimation.

Table 6

Pooled time-series cross-section analysis

We apply the following random effects model to the pooled data of all countries from 1989 to 1995 and to two subsets containing developed and emerging countries separately:

$$Y_{it} = \alpha + \beta' X_{it} + u_i + \varepsilon_{it} ,$$

where Y_{it} is log market volatility in country i and year t, α is constant, β is a 4x1 vector of free parameters, X_{it} is a 4x1 vector of explanatory variables as used in Section V(B), μ_i is the random disturbance characterizing country i and is constant over time, and ε_{it} is an error term. Reported in this table includes the estimated coefficients of explanatory variables and t-statistics (in parentheses) for these coefficient estimates. Industry Concentration = the Herfindahl market industry concentration measure; LEDU = the log value of the average education level of investors; LCAPGDP = the log value of the relative market size measured by 100 times the ratio of total market capitalization to the GDP; LNFIRM = the log value of the number of listed domestic firms; df = the degree of freedom of the model. *, ** and *** indicate significance at the 10%, 5% and 1% levels, respectively.

Data sets	Industry Concentration	LEDU	LCAPGDP	LNFIRM	df	R^2
All	0.122	-0.816***	-0.044	-0.048	128	0.168
	(0.43)	(-3.47)	(-1.11)	(-1.06)		
Developed	0.056	-0.620**	-0.121**	0.005	84	0.169
	(0.13)	(-2.58)	(-2.43)	(0.13)		
Emerging	0.205	-0.723	0.016	-0.023	39	0.054
	(0.44)	(-1.25)	(0.23)	(-0.15)		

D. Non-parametric Tests

Non-parametric techniques are not based on assumptions of variable distributions, which may be unrealistic under certain conditions, and therefore they are desirable in some cases. To provide supplement for our parametric analysis, we compute the Spearman rank correlation coefficient between market volatility and each of the explanatory variables, year by year and in the cross-section. The results are presented in Table 7. A significant, positive correlation coefficient between market industry concentration and market volatility is evident. Both the logarithmic value of the average education level of investors and the logarithmic value of the relative market size are significantly, negatively correlated with market volatility. The logarithmic value of the number of listed firms is moderately related to market volatility. These results are generally consistent with our parametric findings.

Table 7

Spearman rank correlation between market volatility and each of explanatory variables across countries

This table summarizes the Spearman rank-order correlation between log market volatility and each of the explanatory variables. Log market volatility is obtained by taking the log value of 100 times the annualized volatility. We compute cross-sectional Spearman correlation coefficients between log market volatility and various explanatory variables year by year whenever data are available. We then average the correlation coefficients over the period of time examined and report the mean coefficients (Ave. Coefficient) in the table. We also report the percentage of significant correlation coefficients (Percentage of Sig. Coefficients) and the percentage of negative coefficients (Percentage of Neg. Coefficients) among all coefficients for a pair of variables.

	INDUSTRY	LEDU	LCAPGDP	LNFIRM
Period of Time	73-99	88-96	88-97	88-97
Ave. Coefficient	0.459	-0.528	-0.366	-0.299
Percentage of Sig. Coefficients	75%	89%	70%	50%
Percentage of Neg. Coefficients	0%	100%	100%	90%
Average # of Observations	26	19	32	34

V. CONCLUSION

There are large differences in market volatility across international markets. This paper, using index return data for thirty seven international markets from 1973 through 2000, attempts to provide some new insights into the question of why market volatility differs across countries.

Our results indicate that the average education level of investors is the most important factor in explaining cross-country market volatility differences. Specifically, we find that the average education level of investors is significantly and negatively related to market volatility across countries. This factor alone can explain over 36% of cross-country variation of market volatility. This result implies that the better educated the investors in the market, the less volatile the market. We interpret this result as evidence supporting the notion that the collective characteristics of investors in a market play a significant role in shaping market volatility.

We also find some evidence suggesting that market industry concentration, the relative market size and the number of firms listed may also be significantly related to cross-sectional market volatility. The more concentrated the market, the more volatile the market. Smaller stock markets are more volatile. The more firms are listed, the more stable the market will be.

ACKNOWLEDGMENTS

I thank K. C. Chen, the Editor, Thomas Miller, and two anonymous referees for their helpful comments. I am also grateful to Cynthia McDonald for providing part of the data. All remaining errors are my own.

NOTES

1. By comparison, Dow Jones world indexes capture the target of 80% market capitalization for each market, S&P/IFC Global indexes cover about 70% to 75% of total market capitalization, and MSCI world indexes account for only 60% of total market capitalization.
2. Cheung and Ng (1992) fit EGARCH models to 251 stock return series and find $\alpha_2 < 0$ for over 95% of the series.
3. We computed three other measures of volatility: standard deviations of sample returns (SDE), predicted absolute errors (PREE, as proposed by Schwert (1989)), and GARCH estimates. It turns out that our EGARCH volatility estimates are highly correlated with others. We choose to use EGARCH estimates because SDE is not a conditional measure and PREE uses an OLS procedure, which is generally inferior to maximum likelihood estimation (MLE) as used in EGARCH estimation. We use EGARCH instead of GARCH for reasons spelled out in Section III.
4. In this study, we focus on market characteristics rather than outside economic factors or regulatory features. Previous studies have shown that many common economic factors and regulatory features cannot explain the behavior of stock volatility (Roll (1988) and Schwert (1989)).
5. It is well known that there is a substantial "home bias" in equity ownership. French and Poterba (1991) present strong evidence that, even in such highly internationalized markets as the U.S. and Japan, more than ninety percent of the

equity assets of investors are held in their domestic equity markets. As a result, domestic investors hold most domestically listed equities in these markets.

6. School life expectancy is defined as the total number of years of schooling which a child of a certain age can expect to receive in the future, assuming that the probability of his or her being enrolled in school at any particular age is equal to the current enrolment ratio for that age. This indicator shows the overall level of development of an educational system in terms of the number of years of education that a child can expect to achieve. We also tried using the average adult schooling years as a proxy for average investor education level, but the results are quantitatively the same. We report the results based on school life expectancy because more data are available for this variable.
7. For a detailed discussion of pooling time-series cross-section techniques, see Greene (1997).

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