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Emerging equity market volatility

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Abstract

Understanding volatility in emerging capital markets is important for determining the cost of capital and for evaluating direct investment and asset allocation decisions. We provide an approach that allows the relative importance of world and local information to change through time in both the expected returns and conditional variance processes. Our time-series and cross-sectional models analyze the reasons that volatility is different across emerging markets, particularly with respect to the timing of capital market reforms. We find that capital market liberalizations often increase the correlation between local market returns and the world market but do not drive up local market volatility.

Key words: Emerging markets; Volatility; Capital market reforms
JEL classification: G15; G11; G12

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1. Introduction

It is now well known that equities from emerging capital markets have vastly different characteristics than equities from developed capital markets. There are at least four distinguishing features of emerging market returns: higher sample average returns, low correlations with developed market returns, more predictable returns, and higher volatility. Our research focuses on this last feature.

The question of why volatility is so different across emerging equity markets is an important one. In segmented capital markets, risk premiums may be directly related to the volatility of equity returns in the particular market. Higher volatility implies higher capital costs. Higher volatility may also increase the value of the 'option to wait', hence delaying investments. Our research helps understand the forces that shape both the time-series variation and cross-sectional dispersion of volatility in 20 emerging equity markets.

We face a number of challenges in trying to understand volatility in emerging equity markets. First, given the evidence of nonnormalities in the market returns (see Harvey, 1995a), it is unlikely that the standard implementation of autoregressive conditional heteroskedasticity (ARCH) models (see Engle, 1982; Bollerslev, 1986) is fruitful. As a result, we study models that explicitly account for leptokurtosis and skewness. Second, given the existing evidence on return predictablity (see Bekaert and Harvey, 1995), our variance specifications allow for time-varying conditional means. Third, our models of both the means and volatility are designed to let the relative importance of local and world information shift through time as emerging equity markets become more or less integrated into world capital markets. Indeed, part of our goal is to document how this relative influence changes through time. We argue that the increasing impact of world factors on volatility in some countries is consistent with increased market integration.

After studying the time-series properties of volatility, we use our conditional variance estimates to analyze the cross-section of volatility. Following Schwert (1989a,b), we investigate whether the cross-sectional dispersion in volatility is related to a number of macroeconomic and microstructural variables as well as measures linked to financial and economic integration.

We also use our cross-sectional framework to investigate whether capital market liberalization policies affect volatility after controlling for other factors that might affect volatility. The evidence in Kim and Singal (1994), based on average volatilities, suggests that volatility increases. De Santis and İmrohoroğlu (1996) find no significant impact on volatility. As is clear from Bekaert and Harvey (1996a,b), insight on this issue is of great importance for policy makers in developing markets who may be weighing the costs and benefits of various liberalization initiatives.

The paper is organized as follows. Section 2 presents the distributional characteristics of the emerging market data. The third section presents the econometric time-series models. Section 4 contains the empirical results. In the fifth section, we present an analysis of the cross-sectional patterns in volatility and detail how capital market reforms affect volatility. Some concluding remarks are offered in the final section.

2. Data and summary statistics

2.1. Sources and preliminary analysis

Data are available for 20 emerging markets from the International Finance Corporation (IFC) of the World Bank. Summary statistics for U.S. dollar returns are presented in Table 1 for the period January 1976 to December 1992. The statistics include the average (annualized) arithmetic return, annualized standard deviation, and the first-order autocorrelation. Each country's total return index is based on a value-weighted portfolio of securities that represents about 60% of the market's capitalization.

The emerging market returns are characterized by high unconditional volatility ranging from 18% (Jordan) to 104% (Argentina). There are 12 emerging countries with volatility higher than 33% (Argentina, Brazil, Chile, Greece, Mexico, Nigeria, Philippines, Portugal, Taiwan, Turkey, Venezuela, and Zimbabwe). Three additional countries have volatility greater than 30% (Colombia, Indonesia, and Korea). Both the range and the magnitude of the volatilities are much greater than found in developed markets. Using the same sample period, Harvey (1993) finds that volatility in developed markets ranges from 15% (U.S.) to 33% (Hong Kong) with an equally weighted average volatility of 23%.

In focusing on emerging equity markets, a natural concern arises regarding potential survivorship biases. Harvey (1995a) shows that the pre-1981 data in nine countries is 'backfilled' by the IFC. That is, firms are selected in 1981, and their price data are then recorded back to 1976. However, his analysis shows little difference between the 1976–80 data and the later data. More fundamentally, some of the countries in our sample (such as Argentina) have emerged, submerged, and re-emerged. A sample of the most recent 18 years will likely produce biased statistics because this sample does not include the submerged period. This argument is articulated and supported with simulation evidence in Goetzmann and Jorion (1996).

2.2. Distributional characteristics

Evidence that many of the emerging market returns depart from normality is also presented in Table 1. If the data are normally distributed, then the coefficients of skewness and excess kurtosis should be equal to zero. Richardson and Smith (1993) and Harvey (1995a) test for normality of equity returns based on

Table 1
Distributional characteristics of emerging equity market returns

(A) *Distributional characteristics*

Country	Start	Annualized Mean	Annualized Std. dev.	First-order serial correlation	Coefficient of Skewness	Coefficient of Excess kurtosis	GMM χ^2	Bera–Jarque χ^2	Kolmogorov Smirnov
Argentina	76.01	67.87	103.70	0.054	1.961	7.225	24.18^+	574.52^+	2.11^+
					(0.447)	(2.589)	[<0.001]	[<0.001]	
Brazil	76.01	22.10	60.09	0.029	0.519	1.019	12.19	17.97^+	1.23^+
					(0.242)	(0.454)	[0.002]	[<0.001]	
Chile	76.01	36.67	39.48	0.169	0.931	3.126	5.07	112.55^+	0.81
					(0.476)	(2.131)	[0.079]	[<0.001]	
Colombia	85.01	43.64	31.98	0.489	1.709	4.050	31.83^+	112.32^+	1.51^+
					(0.325)	(2.039)	[<0.001]	[<0.001]	
Greece	76.01	7.47	36.13	0.132	1.833	7.327	16.12^+	570.64^+	1.91^+
					(0.443)	(2.114)	[<0.001]	[<0.001]	
India	76.01	20.20	27.16	0.079	0.662	2.242	6.88	57.66^+	1.45^+
					(0.289)	(0.891)	[0.032]	[<0.001]	
Indonesia	90.01	−12.22	32.10	0.285	0.120	−0.219	0.62	0.16	0.51
					(0.262)	(0.447)	[0.732]	[0.924]	
Jordan	79.01	10.75	17.84	0.000	0.452	0.917	7.61	11.60^+	1.59^+
					(0.212)	(0.401)	[0.022]	[0.003]	
Korea	76.01	21.26	32.26	−0.001	0.991	1.961	27.99^+	66.07^+	1.18^+
					(0.301)	(1.280)	[<0.001]	[<0.001]	

Malaysia	85.01	13.84	26.21	0.052	−0.639	2.146	2.13	24.95^{+}	0.43
					(0.519)	(1.478)	[0.345]	[<0.001]	
Mexico	76.01	30.39	44.45	0.248	−0.826	3.694	8.21	139.18^{+}	0.97^{+}
					(0.444)	(1.300)	[0.017]	[<0.001]	
Nigeria	85.01	2.70	36.31	0.085	−1.771	11.230	9.75	554.32^{+}	1.61^{+}
					(1.062)	(3.537)	[0.008]	[<0.001]	
Pakistan	85.01	21.53	23.08	0.250	2.093	9.585	13.93	437.64^{+}	1.58^{+}
					(0.633)	(4.342)	[0.003]	[<0.001]	
Philippines	85.01	45.31	37.99	0.338	0.447	2.122	7.23	21.21^{+}	1.08^{+}
					(0.420)	(0.808)	[0.026]	[<0.001]	
Portugal	86.02	34.57	49.92	0.287	1.578	5.079	11.73	123.69^{+}	1.34^{+}
					(0.575)	(2.326)	[0.003]	[<0.001]	
Taiwan	85.01	34.02	52.62	0.074	0.244	0.959	2.42	4.63	0.97^{+}
					(0.283)	(0.658)	[0.299]	[0.099]	
Thailand	76.01	22.33	25.69	0.114	−0.0962	3.267	10.39	91.06^{+}	1.45^{+}
					(0.505)	(1.352)	[0.006]	[<0.001]	
Turkey	87.01	37.74	73.74	0.232	1.045	0.928	48.00^{+}	15.69^{+}	1.21^{+}
					(0.257)	(0.743)	[<0.001]	[<0.001]	
Venezuela	85.01	32.19	47.06	0.267	0.107	3.093	10.17	38.44^{+}	0.83
					(0.632)	(1.005)	[0.006]	[<0.001]	
Zimbabwe	76.01	7.77	34.09	0.138	0.284	1.892	3.87	33.17^{+}	0.61
					(0.406)	(1.280)	[0.144]	[<0.001]	

Table 1 (continued)

(B) *Power of the GMM normality tests*

		Power against various alternatives				
# obs.	Null critical value	#1 $sk = 0$ $xku = 1.5$	#2 $sk = 0$ $xku = 3.0$	#3 $sk = 0.75$ $xku = -0.05$	#4 $sk = 0.65$ $xku = 4.92$	#5 $sk = 1.53$ $xku = 4.43$
85	19.102	1.96	1.14	85.28	5.26	27.86
192	13.580	1.36	43.14	95.54	11.10	57.54
262	12.454	1.00	86.36	98.64	16.24	70.72
1,000	8.528	100.00	100.00	100.00	89.40	100.00
2,000	7.370	100.00	100.00	100.00	98.98	100.00
5,000	6.435	100.00	100.00	100.00	100.00	100.00
∞	5.990	100.00	100.00	100.00	100.00	100.00

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample ends in December 1992. Heteroskedasticity-consistent standard errors are in parentheses and p-values in brackets. The coefficients of skewness and excess kurtosis are jointly estimated along with the mean and variance in an exactly identified GMM system with four orthogonality conditions. The p-value from a Wald test of the null hypothesis that the coefficients are zero is reported. The variance–covariance matrix of the parameters is heteroskedasticity consistent and corrects for serial correlation using a Bartlett kernel with an optimal bandwidth as in Andrews (1991).

The Wald statistic is asymptotically distributed as a $\chi^2(2)$ variable. The plus superscript denotes a rejection according to the empirical critical value for a test with size 5%. This critical value was generated by applying the tests to 5,000 samples of N(0,1) variables with the relevant number of observations and is reported in panel B. Panel B further reports the power of the test relative to the mixture of normal distributions with various skewness and kurtosis coefficients. Panel A also reports two standard normality tests, the Bera–Jarque (1982) and the Kolmogorov–Smirnov distribution test. P-values based on the $\chi^2(2)$ distribution are reported for the Bera–Jarque test. Empirical critical values are also calculated for the Bera–Jarque test (5.594 for 85 observations and 5.833 for 192 observations) and for the Kolmogorov–Smirnov test (0.878 for 85 observations and 0.873 for 192 observations). These tests are in most cases more powerful than the GMM test. The plus superscripts denote rejections according to the 5% empirical critical values.

Hansen's (1982) generalized method of moments (GMM). The following system of equations is estimated for each asset i:

$$\begin{aligned} e_{1it} &= r_{it} - \mu_i\,, \\ e_{2it} &= (r_{it} - \mu_i)^2 - \sigma_i^2\,, \\ e_{3it} &= [(r_{it} - \mu_i)^3]/\sigma_i^{3/2} - sk_i\,, \\ e_{4it} &= [(r_{it} - \mu_i)^4]/\sigma_i^{2} - 3 - xku_i\,, \end{aligned} \tag{1}$$

where μ is the mean, σ^2 is the variance, sk is the skewness, xku is the excess kurtosis, and $e_t = \{e_{1it}\ e_{2it}\ e_{3it}\ e_{4it}\}'$ represents the disturbances, where $\mathrm{E}[e_t] = \mathbf{0}$. There are four orthogonality conditions and four parameters, implying that the model is exactly identified. The null hypothesis that the coefficients of skewness and excess kurtosis are zero is tested with a Wald test.[1] We also present the more traditional Bera–Jarque (1982) and Kolmogorov–Smirnov tests for normality.

The GMM test suggests that the null hypothesis of unconditional normality can be rejected at the 5% level in 15 of the 20 emerging markets when measured in U.S. dollars. The Bera–Jarque (Kolmogorov–Smirnov) test provides evidence against the hypothesis of normality in 18 (15) of 20 countries. These results are consistent with Harvey (1995a) and Claessens, Dasgupta, and Glen (1995). Monte Carlo analysis of the GMM test statistics suggests that only five countries (Argentina, Colombia, Greece, Korea, and Turkey) exceed the empirical critical value for a test with size 5%. There are two additional countries, Brazil and Thailand, whose test statistic is very close to the empirical cutoff. However, the Monte Carlo analysis of the Bera–Jarque and Kolmogorov–Smirnov tests suggests that 18 and 15 countries, respectively, exceed the critical value.

The second panel in Table 1 investigates the power of the GMM normality tests. The data generation process under the null is a standard normal distribution. Under the alternative, we use a mixture of normal distributions model with a mean equal to zero and a variance equal to unity but with five different configurations of the skewness and kurtosis coefficients. For the sample sizes that we face and given the high point estimates, we believe that the data are more likely to have been drawn from a distribution that departs from normality.[2]

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[1]Richardson and Smith (1993) present this general framework. However, our weighting matrix is based on the spectral density at frequency zero with an optimal bandwidth which follows Andrews (1991). An alternative approach, presented in Harvey (1995a), is to set sk and xku equal to zero and estimate an overidentified system. This results in a χ^2 test with two degrees of freedom.

[2]Analysis of the power of the Bera–Jarque and Kolmogorov–Smirnov tests are available on request.

3. A world factor model of conditional variances

3.1. The general model

Let $r_{i,t}$ represent the arithmetic excess return on the national equity index of country i in U.S. dollars. Our model has the following general form:

$$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t}\,, \tag{2}$$

$$\varepsilon_{i,t} = v_{i,t-1}\varepsilon_{w,t} + e_{i,t}\,, \tag{3}$$

$$(\sigma'_{i,t})^2 = \mathrm{E}[e_{i,t}^2 \mid \boldsymbol{I}_{t-1}] = c_i + \alpha_i(\sigma'_{i,t-1})^2 + \beta_i e_{i,t-1}^2 + \gamma_i S_{i,t} e_{i,t-1}^2\,, \tag{4}$$

$$e_{i,t} = \sigma'_{i,t} z_{i,t}\,, \tag{5}$$

where $\boldsymbol{I}_{t-1}$ is the information available at time $t-1$. The conditional mean return for country i is given by $\mu_{i,t-1}$. The unexpected portion of country i's return, $\varepsilon_{i,t}$, is driven by in part by world shocks, $\varepsilon_{w,t}$, as well as a purely idiosyncratic shock, $e_{i,t}$. The dependence of local shocks on world shocks is determined by $v_{i,t-1}$. The local idiosyncratic standard deviation is $\sigma'_{i,t}$ and $z_{i,t}$ is a standardized residual with zero mean and unit variance. Finally, $S_{i,t}$ is an indicator variable that takes on the value of one when the idiosyncratic shock is negative and zero otherwise.

The model that describes the world market returns and variances is a special case of (2)–(5), with $i = w$, $\sigma'_{i,t} = \sigma_{w,t}$, $v_{w,t-1} = 0$, and $\mu_{w,t-1} = \boldsymbol{\delta}'_w \mathbf{X}_{t-1}$, where $\mathbf{X}_{t-1}$ represents a set of world information variables including a constant, the world market dividend yield in excess of the 30-day Eurodollar rate, the default spread (Moody's Baa minus Aaa bond yields), the change in the term structure spread (U.S. ten-year bond yield minus three-month T-bill yield), and the change in the 30-day Eurodollar rate. These variables are designed to capture fluctuations in expectations about the world business cycle (see Harvey, 1991). All of these information variables are lagged.

The generalized autoregressive conditional heteroskedasticity or GARCH(1,1) specification in (4) is the Glosten, Jagannathan, and Runkle (1993) and Zakoian (1994) model, which accommodates asymmetries in the volatility of equity returns. Engle and Ng (1993) find that this model performs better than other asymmetric models in Monte Carlo experiments. It is typically found that $\gamma_i > 0$, that is, negative shocks increase volatility by more than positive shocks (see Black, 1976; Christie, 1982; Schwert, 1989a; Nelson, 1991; Glosten, Jagannathan, and Runkle, 1993). One explanation is that the leverage of the firm increases with negative returns, inducing a higher volatility. These leverage effects will most likely be found in firms that already employ considerable debt financing. While we do not have data on the debt–equity ratios of individual firms in the emerging markets, many of the countries themselves are highly levered. Hence, it seems important to allow for the possibility of asymmetries in the variance function.

Note that for the emerging markets, asymmetry is defined through the idiosyncratic shock. Any potential asymmetry in the world market return variances enters through $\varepsilon_{w,t}$.

Furthermore, we assume

$$\mathrm{E}[e_{i,t}e_{j,t}\,|\,\mathbf{I}_{t-1}] = 0\,, \quad \forall i \neq j\,, \tag{6}$$

$$\mathrm{E}[e_{i,t}\varepsilon_{w,t}\,|\,\mathbf{I}_{t-1}] = 0\,, \quad \forall i\,. \tag{7}$$

Hence, the model implies

$$\mathrm{E}[\varepsilon_{i,t}^2\,|\,\mathbf{I}_{t-1}] = \sigma_{i,t}^2 = v_{i,t-1}\sigma_{w,t}^2 + (\sigma_{i,t}^{\prime})^2, \tag{8}$$

$$\mathrm{E}[\varepsilon_{i,t}\varepsilon_{w,t}\,|\,\mathbf{I}_{t-1}] = v_{i,t-1}\sigma_{w,t}^2 = \sigma_{iw,t}\,. \tag{9}$$

We will explore two parameterizations for $\mu_{i,t-1}$ and $v_{i,t-1}$ so as to allow for both local and world influences in the mean and the variance. In both cases, the influence on volatility is allowed to change through time as a function of local variables that contain information regarding the country's degree of financial and economic integration with world markets. In the first parameterization in Section 3.2, $\mu_{i,t-1}$ and $v_{i,t-1}$ are assumed to be linear in the information variables. The second parameterization proposes a nonlinear model. Section 3.3 discusses our distributional assumptions about the scaled residuals, and Section 3.4 outlines the construction of the likelihood function. Finally, Section 3.5 describes our specification tests.

3.2. Conditional mean and variance specification

3.2.1. The linear model

In integrated world capital markets, shocks to the world market return affect all countries that have nonzero covariances with the world market. Bekaert and Harvey (1995) develop a model of the conditional mean return in emerging markets that allows for time-varying influences of both local and world factors. We apply the same type of intuition to our variance model. That is, as a market becomes more integrated, *both* the conditional mean and the variance should be more influenced by world factors. Our first model focuses primarily on the conditional variance. We let $\mu_{i,t-1}$ and $v_{i,t-1}$ be linear in the information variables (*linear model*):

$$\mu_{i,t-1} = \boldsymbol{\delta}_{i,1}^{\prime}\mathbf{X}_{i,t-1} + \boldsymbol{\delta}_{i,2}^{\prime}\mathbf{X}_{t-1}\,, \tag{10}$$

$$v_{i,t-1} = \boldsymbol{q}_{i,0} + \boldsymbol{q}_{i,1}^{\prime}\mathbf{X}_{i,t-1}^{*\prime}\,, \tag{11}$$

where $\mathbf{X}_{t-1}$ is defined as before and $\mathbf{X}_{i,t-1}$ represents the local information variables: a constant, the equity return, the exchange rate change, the dividend yield, the ratio of equity market capitalization to gross domestic product (GDP), and the ratio of trade to GDP, all of which are lagged. Hence, the conditional mean depends on both local and global variables but the weights are kept fixed over time. The evidence in Garcia and Ghysels (1994) suggests that if expected returns in emerging markets are conditioned exclusively on world information variables, there is evidence of structural instability in linear models.

In Eq. (11), $\mathbf{X}^*_{i,t-1}$ includes market capitalization to GDP and the size of the trade sector (exports plus imports divided by GDP), both of which might proxy for the degree of integration. When capital markets open up to foreign investment, the change in the marginal investor typically increases the ratio of market capitalization to GDP. International trade may enhance the cross-country correlation between consumption and business cycles which, in turn, can lead to prices of risk and/or risk exposures moving together, even when capital markets are segmented. Hence, the dependence of the conditional variance on world factors is allowed to change with the degree of integration.

3.2.2. The nonlinear model

In the nonlinear model, the influence of local and world information on the emerging market's expected returns is also allowed to change through time. Following Bekaert and Harvey (1995), we let

$$\mu_{i,t-1} = \theta_{i,t-1}\kappa_i\boldsymbol{\delta}'_w\mathbf{X}_{t-1} + (1-\theta_{i,t-1})(\boldsymbol{\delta}'_i\mathbf{X}_{i,t-1})\,. \tag{12}$$

The parameter $\theta_{i,t-1}$ represents the importance of the world information variables. We restrict

$$\theta_{i,t-1} = \frac{(\boldsymbol{\lambda}'_i\mathbf{X}^*_{i,t-1})^2}{1+(\boldsymbol{\lambda}'_i\mathbf{X}^*_{i,t-1})^2} \tag{13}$$

to fall in the range [0,1]. Note that the nonlinear relation in (13) implies that the relation between $\mathbf{X}^*_{i,t-1}$ and $\theta_{i,t-1}$ need not be monotonic over the sample. This is useful when market capitalization increases because of local factors, such as the introduction of a private pension plan.

We also let

$$v_{i,t-1} = \xi_i\psi_{i,t-1}\,, \tag{14}$$

where ξ_i is a scale parameter and $\psi_{i,t-1}$ represents the importance of the world shock, which is also restricted to fall in the [0,1] range:

$$\psi_{i,t-1} = \frac{(\boldsymbol{\zeta}'_i\mathbf{X}^*_{i,t-1})^2}{1+(\boldsymbol{\zeta}'_i\mathbf{X}^*_{i,t-1})^2}\,. \tag{15}$$

As with $\theta_{i,t-1}$, $\psi_{i,t-1}$ is a time-varying, nonlinear function of local information variables that proxy for the degree of integration.

This nonlinear model is related to, but different from, the factor ARCH models of Engle, Ng, and Rothchild (1990, 1992), King, Sentana, and Wadhwani (1994), and Diebold and Nerlove (1989). In these models, a world factor is allowed to influence volatility at a constant rate. In the special case where $\theta_{i,t-1} = \psi_{i,t-1} = 1$ for all t, the variance model is similar to the Engle, Ng, and Rothchild model. If $\theta_{t-1} = 1$ and $\boldsymbol{\delta}'_w \mathbf{X}_{t-1}$ is the world market premium, then the κ_i coefficient in the conditional mean specification can be interpreted as the constant factor loading in a world capital asset pricing model. These factor models also imply the restriction $\kappa_i = \xi_i$. We perform tests of $\kappa_i = \xi_i$ and $\theta_{i,t-1} = \psi_{i,t-1}$ both jointly and separately. In contrast to the factor ARCH models, our specification allows for both local and world influences in the mean and the variance. Importantly, the influence is allowed to change through time as a function of local variables that contain information regarding the country's degree of financial and economic integration with world economic markets.

3.2.3. Implications for conditional correlations

The covariance dynamics of the model in Eq. (9) have two important implications. First, the covariance with the world market return is positively related to the degree of market integration. Second, the covariance with the world return increases in times of high world market volatility. As such, our results contribute to the recent literature on international stock market linkages.[3]

The two stylized facts often noted in this literature are that the process of globalization and deregulation has increased the correlations between stock markets over time and that the correlation between markets rises in periods when the volatility of markets is large (for example, around the October 1987 crash). However, the empirical evidence, particularly on the first fact, is mixed. For example, although Longin and Solnik (1995) document an upward trend in international correlations, King, Sentana, and Wadhwani (1994) argue that the increase in correlations may be transitory and related to the October 1987 crash.

In the empirical section, we focus on two statistics. The first is the correlation of the emerging market return with the world market return. The world market correlation in our model is given by

$$\rho_{it} = v_{i,t-1} \frac{\sigma_{w,t}}{\sigma_{i,t}} \,. \tag{16}$$

Hence, correlations increase when markets become more integrated or when world market volatility is high relative to local volatility. The latter mechanism is the only one present in the model of King, Sentana, and Wadhwani (1994) to induce higher correlations between markets. A trend in the correlations can only arise when the factors in their model exhibit integrated GARCH behavior. Below, we

[3]See King and Wadhwani (1990), King, Sentana, and Wadhwani (1994), Longin and Solnik (1995), and Karolyi and Stulz (1996). Erb, Harvey, and Viskanta (1994) show that correlations are higher in down markets and during recessions.

graph the conditional correlations implied by the model. We also investigate their behavior post-crash and post-liberalization relative to the full sample.

Second, we examine the proportion of local variance accounted for by world factors. The following variance ratio is computed:

$$VR_{i,t} = \frac{v_{i,t-1}^2 \sigma_{w,t}^2}{\sigma_{i,t}^2} \in [0,1]\,. \tag{17}$$

Using the definition in (9), we can equivalently write:

$$VR_{i,t} = \frac{v_{i,t-1} \sigma_{iw,t}}{\sigma_{i,t}^2}\,. \tag{18}$$

The variance ratio can be decomposed into three pieces representing the degree of integration, the correlation, and the volatility ratio, respectively,

$$\xi_i \psi_{i,t-1}\,, \quad \frac{\sigma_{iw,t}}{\sigma_{i,t}\sigma_{w,t}}\,, \quad \frac{\sigma_{w,t}}{\sigma_{i,t}}\,.$$

$VR_{i,t}$ gives an indication of the proportion of the conditional variance that cannot be explained by local factors. We will also examine the time variation in $VR_{i,t}$ post-crash and post-liberalization.

3.3. Distributional assumptions

We show in Section 3.4 that under certain conditions the joint likelihood of all the data collapses into the univariate models described in (2)–(5). This makes it particularly easy to accommodate different distributional assumptions in the standardized residuals. In particular, there are three different distributional assumptions in the general model:

$$\begin{aligned}
&\text{Model I}: && z_{i,t} \mid \boldsymbol{I}_{t-1} \sim \mathrm{N}(0,1)\,, \\
&\text{Model II}: && z_{i,t} \mid \boldsymbol{I}_{t-1} \sim t_{v_i(0,1)}\,, \\
&\text{Model III}: && z_{i,t} \mid \boldsymbol{I}_{t-1} \sim \begin{cases} \mathrm{N}(\mu_{i,1}, \sigma_{i,1}), & \text{w.p. } p_i\,, \\ \mathrm{N}(\mu_{i,2}, \sigma_{i,2}), & \text{w.p. } (1-p_i)\,. \end{cases}
\end{aligned} \tag{19}$$

The first model is the standard normal formulation. The second model introduces a t-distribution with v_i degrees of freedom. This is a one-parameter extension of model I. While able to accommodate fat tails, the assumed distribution in model II is symmetric.

The third model is designed to capture both fat tails and skewness (which quite a few of the emerging markets exhibit). Model III is a parsimonious version of semiparametric ARCH (SPARCH) (see Engle and Gonzalez-Rivera, 1991; Gray, 1995). Since in ARCH models the conditional mean of the standardized residuals is equal to zero and the conditional variance is equal to one, additional constraints need to be imposed:

$$\mu_{i,2} = \frac{-p_i\mu_{i,1}}{1-p_i},$$
$$\sigma_{i,2} = \sqrt{\frac{1-p_i\sigma_{i,1}^2-(p_i\mu_{i,1}^2+(1-p_i)\mu_{i,2}^2)}{1-p_i}}. \tag{20}$$

Hence, this model is a three-parameter extension of the standard model.

3.4. Estimation

Let $\boldsymbol{r}_t = [r_{w,t}, r_{1,t}, r_{2,t}, \ldots, r_{N,t}]'$ and let $\boldsymbol{Z}_t$ represent the vector of instrumental variables used in the model. Hence, the information set $\boldsymbol{I}_t$ in our model consists of $[\boldsymbol{r}_t', \boldsymbol{Z}_t']'$. Rather than maximizing the joint likelihood of all the data, we simplify the problem in two major ways.

First, we do not model the dynamic behavior of $\boldsymbol{Z}_t$ and maximize the conditional likelihood function of the returns data. Second, we estimate the resulting likelihood function for the return data in two stages. In the first stage, we estimate the world market return model. The second stage estimates the model (2)–(5) country by country, conditioning on the world market model estimates. We report White (1982) standard errors that are robust to misspecification of the distribution of the error terms. However, we do not correct for the sampling error of the world market model parameters in the first-stage estimation. This approach yields consistent but not necessarily efficient estimates.

Appendix A formally shows how the joint likelihood function of all the data collapses to 21 univariate models. Important assumptions underlying our country-by-country estimation are: (a) the density of $r_{w,t}$ conditional on $\boldsymbol{I}_{t-1}$ (for our nonlinear model, for example) depends only on $\boldsymbol{\theta}_w = [\boldsymbol{\delta}_w', c_w, \alpha_w, \beta_w]'$ and not on any $\boldsymbol{\theta}_i = [\boldsymbol{\delta}_i', c_i, \alpha_i, \beta_i, \kappa_i, \zeta_i, \boldsymbol{\lambda}_i', \boldsymbol{\xi}_i']'$ for all i; (b) the density of $r_{i,t}$ conditional on I_{t-1} and $r_{w,t}$ depends on $[\boldsymbol{\theta}_w', \boldsymbol{\theta}_i']'$ and not on any θ_j, $j \neq i$; and (c) the individual idiosyncratic shocks are independent across emerging markets and independent of the world market shock. In the case of normal innovations, this follows from the assumptions in (6) and (7).

3.5. Specification tests

Our specification tests are inspired by the presentation in Nelson (1991). Consider the standardized residuals, $\hat{z}_{i,t} = \hat{e}_{i,t}/\hat{\sigma}_{i,t}$, for $i = 1, \ldots, N, w$. Under the null hypothesis that the model is correctly specified,

(a) $\mathrm{E}[\hat{z}_{i,t}] = 0$,

(b) $\mathrm{E}[\hat{z}_{i,t}^2 - 1] = 0$,

$$\begin{aligned}
&\text{(c)} \quad \mathrm{E}[\hat{z}_{i,t}\hat{z}_{i,t-j}] = 0\,, && j = 1,\ldots,k\,,\\
&\text{(d)} \quad \mathrm{E}[\hat{z}_{i,t}^3 - sk_i] = 0\,, &&\\
&\text{(e)} \quad \mathrm{E}[\hat{z}_{i,t}^4 - ku_i] = 0\,, &&\\
&\text{(f)} \quad \mathrm{E}[(\hat{z}_{i,t}^2 - 1)(\hat{z}_{i,t-j}^2 - 1)] = 0\,, && j = 1,\ldots,k\,,
\end{aligned} \tag{21}$$

where sk_i represents the skewness parameter and ku_i is the kurtosis. The correct specification of the conditional mean is implicit in (21c). The conditional variance is in (21f). In (21a,b,d,e), the unconditional moments of $\hat{z}_i$ are compared to those predicted by the model.

In the standard setup (model I), $sk_i = 0$ and $ku_i = 3$. For model II, the skewness is also equal to zero but the kurtosis is $ku_i = 3(\hat{v}_i - 2)/(\hat{v}_i - 4)$. For the SPARCH model, the skewness is

$$sk_i = \hat{p}_i(\hat{\mu}_{i,1}^3 + 3\hat{\sigma}_{i,1}^2\hat{\mu}_{i,1}) + (1 - \hat{p}_i)(\hat{\mu}_{i,2}^3 + 3\hat{\sigma}_{i,2}^2\hat{\mu}_{i,2})\,, \tag{22}$$

and the kurtosis is

$$ku_i = \hat{p}_i(6\hat{\mu}_{i,1}^2\hat{\sigma}_{i,1}^2 + 3\hat{\sigma}_{i,1}^4 + \hat{\mu}_{i,1}^4) + (1 - \hat{p}_i)(6\hat{\mu}_{i,2}^2\hat{\sigma}_{i,2}^2 + 3\hat{\sigma}_{i,2}^4 + \hat{\mu}_{i,2}^4)\,. \tag{23}$$

Notice that the SPARCH model collapses to model I ($ku_i = 3$, $sk_i = 0$) when $p_i = 1$, $\mu_{i,1} = 0$, and $\sigma_{i,1} = 1$.

Much like our normality tests, it is straightforward to use the generalized method of moments to conduct specification tests. However, in contrast to the normality tests, the specification tests will be based on moments from generated time series. The conditional mean specification is tested by setting $k = 4$ and obtaining a χ^2 statistic from (21c). A similar test is conducted on the conditional variance in (21f). The distributional assumptions of the model are tested by examining (21a,b,d,e). This results in a χ^2 statistic with four degrees of freedom. It is also possible to jointly test all of the restrictions. With $k = 4$, there are 12 degrees of freedom in the test statistic.

In Appendix B, we examine the small-sample distribution of these test statistics. In the empirical work, we will present p-values based on the χ^2-distribution, but will also indicate rejections (at the 5% level) relative to the small-sample empirical distribution.

4. The time variation of volatility in emerging markets

We structure our discussion of the results in four parts. First, we discuss the estimation of the world market return model. Second, we examine the parameter estimates of the world factor model and the diagnostics. Third, we detail the time-varying correlation with the world and the importance of world factors. Finally, we examine two individual countries in greater detail.

4.1. The world market return model

Since the world market variances, shocks, and expected returns are critical inputs in our univariate emerging market models, it is important to select the best model. With three distributional assumptions and the potential presence of asymmetry, we estimate six different models. Table 2 summarizes the specification tests. There is evidence against the two models that assume a t-distribution for the standardized residuals, but none against any of the other four models. There is pronounced asymmetry: the likelihood ratio tests reject the null hypothesis of no asymmetry in all three cases and the γ_w coefficients are highly positive. In fact, the β_w coefficients are small but negative so that the asymmetric world market return model displays strong asymmetry: the conditional variance decreases following a positive shock.

While the expected return estimates are very highly correlated across all models, the conditional variance process depends critically on whether asymmetry is allowed. The correlation between the conditional variances resulting from estimating the same GARCH model with different distributional assumptions is between 0.96 and 0.98. However, the correlation between the conditional variances resulting from the normal and from the normal/asymmetric model is only 0.39. These conditional variances are graphed in Fig. 1.

To obtain an absolute ranking of the fit of the different models, we regress the squared residuals onto the estimated conditional variances as in Pagan and Schwert (1990). The models accommodating asymmetry have substantially higher R^2s than the other models. The highest R^2 was recorded for the normal model with asymmetry, which we therefore select as the world market return model to be used in the remainder of the paper.

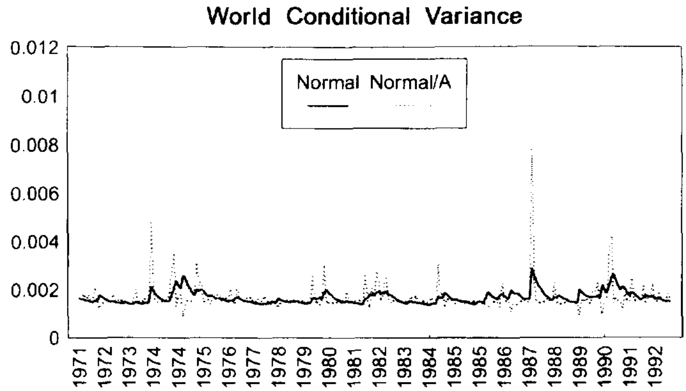
4.2. World factor model and diagnostics

To choose among the 12 specifications (six each for the linear and nonlinear models: there are three different distributional assumptions as well as the asymmetry possibility),[4] we use the four specification tests. When the specification tests are ambiguous, we follow Pagan and Schwert (1990) and regress e_{it}^2 on σ_{it}^2 and choose the model with the highest R^2.

Table 3 presents the specification tests and model diagnostics for the world factor model. The SPARCH distributional assumption is used in six of the 19 countries and the normal is used in the rest. Significant variance asymmetry is

[4] A number of steps were taken to maximize the chance that we achieved the global optimum in the estimation. We begin with the simplest model (normal without asymmetry) and estimate using at least ten different sets of starting values. We use the final parameter estimates as starting values in the more complex models. In addition, the candidate global optima for each model are 'confirmed' by shocking the parameters in the vicinity of the candidate global optimum.

(A)



(B)

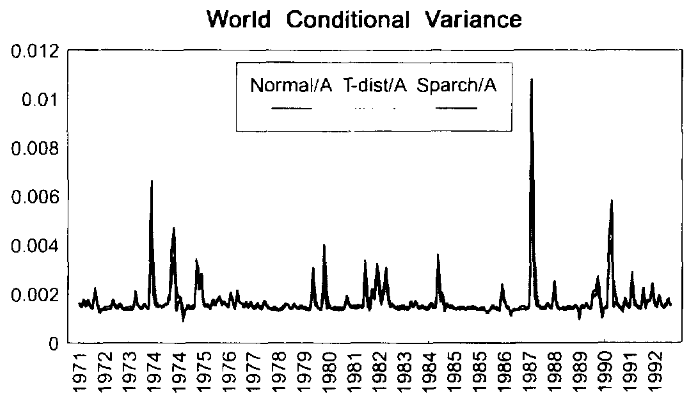


Fig. 1. World conditional variances.

Panel A presents the fitted world conditional variance from the GARCH model with normal standardized residuals with and without asymmetry. The model (with asymmetry) is

$$r_{w,t} = \mu_{w,t-1} + \varepsilon_{w,t}, \quad \sigma^2_{w,t} = c_w + \alpha_w \sigma^2_{w,t-1} + \beta_w \varepsilon^2_{w,t-1} + \gamma_w S_{w,t} \varepsilon^2_{w,t-1}, \quad \varepsilon_{w,t} = \sigma_{w,t} z_{w,t},$$

where $r_{w,t}$ is the U.S. dollar return on the Morgan Stanley Capital International World portfolio, $\mu_{w,t-1}$ is the conditional mean, $S_{w,t}$ is an indicator variable which takes on the value of one when the unexpected mean return is negative and zero otherwise, and $z_{w,t}$ is a standardized residual with zero mean and unit variance. The conditioning information for the mean includes: a constant, the world market dividend yield in excess of the 30-day Eurodollar rate, the default spread (Moody's Baa minus Aaa bond yields), the change in the term structure spread (U.S. ten-year bond yield minus three-month T-bill), and the change in the 30-day Eurodollar rate. In panel B, the fitted values for the conditional variance with asymmetry are presented with three different assumptions on the error structure: normal, t-distribution, and SPARCH (mixture of normals).

Table 2
The world market return model

The following model is estimated:

$$r_{w,t} = \mu_{w,t-1} + \varepsilon_{w,t}, \quad \sigma^2_{w,t} = c_w + \alpha_w \sigma^2_{w,t-1} + \beta_w \varepsilon^2_{w,t-1} + \gamma_w S_{w,t} \varepsilon^2_{w,t-1}, \quad \varepsilon_{w,t} = \sigma_{w,t} z_{w,t},$$

where $\mu_{w,t-1} = \delta'_w \mathbf{X}_{t-1}$ and $\mathbf{X}_{t-1}$ represents a set of world information variables which includes a constant, the world market dividend yield in excess of the 30-day Eurodollar rate, the default spread (Moody's Baa minus Aaa bond yields), the change in the term structure spread (U.S. ten-year bond yield minus three-month T-bill yield), and the change in the 30-day Eurodollar rate. All of these information variables are lagged. The unexpected portion of the world return is $\varepsilon_{w,t}$, $\sigma^2_{w,t}$ is the fitted variance, $S_{w,t}$ is an indicator variable which takes on the value of one when the shock to the world return is negative and zero otherwise, and $z_{w,t}$ is a standardized residual with zero mean and unit variance.

	Specification tests				Asymmetry tests	
Model	Mean	Moment	Variance	Joint	γ_w	χ^2
Normal	2.538	4.984	0.119	8.513		
	[0.638]	[0.289]	[0.998]	[0.774]		
Normal/asymmetry	1.937	4.925	0.681	8.124	0.269	10.993
	[0.747]	[0.295]	[0.954]	[0.775]	(0.124)	[0.001]
T-distribution	2.541	37.380	0.787	50.470		
	[0.637]	[<0.001]	[0.940]	[<0.001]		
T-distribution/ asymmetry	1.920	22.560	2.753	32.610	0.297	4.588
	[0.750]	[<0.001]	[0.600]	[0.001]	(0.164)	[0.032]
SPARCH	2.460	1.755	0.264	6.632		
	[0.652]	[0.781]	[0.992]	[0.877]		
SPARCH/ asymmetry	1.893	1.147	3.385	9.076	0.331	4.291
	[0.755]	[0.889]	[0.496]	[0.690]	(0.092)	(0.038)

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample is February 1976 to December 1992. Heteroskedasticity-consistent standard errors are in parentheses and p-values are in brackets. The means test is based on the first four autocovariances of the scaled residuals (21c); the variance test is based on the first four autocovariances of the squared scaled residuals (21f); the moments tests is based on four moments (mean, variance, skewness, and kurtosis (21a,b,d,e)); and the joint test is based on all the restrictions.

found in ten countries. In three of these ten cases, the asymmetry parameter is negative, implying that a large shock decreases conditional variance. In all but four countries, the nonlinear model is rejected in favor of the linear model but the R^2 regression test had to be used for six countries.

The specification tests suggest very few rejections. We implemented Monte Carlo analysis to determine the empirical cutoffs for the test statistic (see Appendix Table A.1). The means test suggests a rejection in Jordan; the moments test rejects the model for Portugal and Turkey; and the variance test provides evidence against the models in Pakistan and Taiwan. Interestingly, the joint test suggests rejection for only one country, Portugal.

Table 3
World factor model: Parameters and diagnostics

We estimate the following general model:

$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t}$ (2) $\varepsilon_{i,t} = v_{i,t-1}\varepsilon_{w,t} + e_{i,t}$ (3) $(\sigma'_{i,t})^2 = c_i + \alpha_i(\sigma'_{i,t-1})^2 + \beta_i e^2_{i,t-1} + \gamma_i S_{i,t} e^2_{i,t-1}$ (4) $e_{i,t} = \sigma'_{i,t} z_{i,t}$ (5)

where $\mu_{i,t-1}$ is the conditional mean return. The unexpected portion of country i's return, $\varepsilon_{i,t}$, is driven by a portion due to world shocks, $\varepsilon_{w,t}$, and a purely idiosyncratic shock, $e_{i,t}$. The dependence of local shocks on world shocks is determined by the parameter $v_{i,t-1}$. The local idiosyncratic standard deviation is $\sigma'_{i,t}$, $z_{i,t}$ is a standardized residual with zero mean and unit variance, and $S_{i,t}$ is an indicator variable that takes on the value of one when the idiosyncratic shock is negative and zero otherwise. A similar model is estimated for the world market return (denoted with w subscripts) based on (2), (3), and (5). The three-digit model code is defined as follows: the first number represents the distributional assumptions (1 = normal, 2 = t-distribution, and 3 = SPARCH), and the second number denotes the assumptions on the conditional mean and the variance (1 = linear model, 2 = nonlinear model). More specifically

Model 1 (linear)

$\mu_{i,t-1} = \boldsymbol{\delta}'_{i,1}\mathbf{X}_{i,t-1} + \boldsymbol{\delta}'_{i,2}\mathbf{X}_{t-1}$ (10) and $v_{i,t-1} = \boldsymbol{q}_{i,0} + \boldsymbol{q}'_{i,1}\mathbf{X}^{*\prime}_{i,t-1}$ (11)

where $\mathbf{X}_{t-1}$ and $\mathbf{X}_{i,t-1}$ denote world and local information respectively and

Model 2 (nonlinear)

$\mu_{i,t-1} = \theta_{i,t-1}\kappa_i\boldsymbol{\delta}'_w\mathbf{X}_{t-1} + (1 - \theta_{i,t-1})(\boldsymbol{\delta}'_i\mathbf{X}_{i,t-1})$ (12) where $\theta_{i,t-1} = \dfrac{(\boldsymbol{\lambda}'_i\mathbf{X}^*_{i,t-1})^2}{1 + (\boldsymbol{\lambda}'_i\mathbf{X}^*_{i,t-1})^2}$ (13) $v_{i,t-1} = \xi_i\psi_{i,t-1}$ (14) $\psi_{i,t-1} = \dfrac{(\boldsymbol{\zeta}'_i\mathbf{X}^*_{i,t-1})^2}{1 + (\boldsymbol{\zeta}'_i\mathbf{X}^*_{i,t-1})^2}$ (15)

The third number represents whether asymmetry is accommodated (1) or not (0). The following specification tests are conducted. The means and variance tests are based on (21c) and (21f), respectively, testing the serial correlation properties of the standardized residuals and the squared standardized residuals. The moments test is based on (21a,b,d,e). The joint test is based on (21a–f).

Three Wald tests are reported. These tests depend on whether the linear or nonlinear model is being estimated. Wald test I for the linear model is a test of the significance of the global information in the mean, and for the nonlinear model it is a test of whether $\kappa_i = \zeta_i$; Wald test II for the linear model is a test of the significance of the variance parameters in $v_{i,t-1}$, and for the nonlinear model it is a joint test of $\theta_{i,t} = \psi_{i,t}$; Wald test III: linear model – test of the significance of trade and size variables ($\mathbf{X}^*$) in $v_{i,t-1}$, nonlinear model – joint test of $\kappa_i = \zeta_i$ and $\theta_{i,t} = \psi_{i,t}$. The reported parameters are also dependent on the model. The column κ_i is only applicable to the nonlinear model. The column q_{i0}/ξ_i denotes q_{i0} (the first element in $v_{i,t-1}$ in the linear model) and ξ_i in the nonlinear model. The column γ_i presents the asymmetry parameter when this model is chosen.

		Specification tests				Wald tests			Parameters		
Country	Model	Mean	Moment	Variance	Joint	I	II	III	κ_i	q_{i0}/ξ_i	γ_i
Argentina	310	0.867 [0.929]	0.885 [0.927]	2.287 [0.683]	8.609 [0.736]	4.878 [0.300]	0.843 [0.839]	0.458 [0.795]	—	1.519 (2.932)	—
Brazil	111	2.671 [0.614]	2.997 [0.558]	5.970 [0.201]	12.729 [0.389]	3.642 [0.457]	0.544 [0.909]	0.039 [0.981]	—	−0.537 (4.017)	0.353 (0.163)
Chile	110	9.503 [0.050]	1.607 [0.808]	0.629 [0.960]	12.739 [0.388]	4.218 [0.377]	13.743 [0.003]	1.522 [0.467]		0.376 (1.893)	—
Colombia	110	4.411 [0.353]	8.103 [0.088]	3.288 [0.511]	18.933 [0.090]	16.397 [0.003]	5.372 [0.146]	5.029 [0.081]	—	−3.354 (1.659)	—
Greece	310	1.254 [0.869]	1.208 [0.877]	2.762 [0.598]	6.749 [0.874]	17.486 [0.002]	4.350 [0.226]	2.052 [0.358]	—	−1.691 (1.396)	—
India	311	6.696 [0.153]	0.856 [0.931]	4.226 [0.376]	14.575 [0.266]	1784.300 [<0.001]	>10,000 [<0.001]	>10,000 [<0.001]	—	−2.146 (0.000)	−0.201 (0.001)
Jordan	320	12.333*+ [0.015]	0.855 [0.931]	4.472 [0.346]	21.289* [0.046]	2.240 [0.134]	>10,000 [<0.001]	>10,000 [<0.001]	0.392 (0.132)	0.174 (0.112)	—
Korea	311	0.506 [0.973]	0.274 [0.991]	1.539 [0.820]	2.553 [0.998]	15.420 [0.004]	6.685 [0.083]	1.060 [0.589]	—	0.483 (1.980)	0.195 (0.103)
Malaysia	110	5.714 [0.222]	1.752 [0.781]	5.373 [0.251]	12.635 [0.396]	5.797 [0.215]	46.449 [<0.001]	7.651 [0.022]		3.660 (0.997)	—
Mexico	320	4.363 [0.359]	1.120 [0.891]	0.561 [0.967]	7.381 [0.831]	5.325 [0.021]	11.950 [0.008]	36.094 [<0.001]	−1.483 (1.079)	1.582 (0.753)	—

Table 3 (continued)

Country	Model	Specification tests				Wald tests			Parameters		
		Mean	Moment	Variance	Joint	I	II	III	κ_i	q_{i0}/ξ_i	γ_i
Nigeria	111	1.904	8.461	1.440	13.965	1018.500	2690.200	484.620	—	−0.743	2.864
		[0.753]	[0.076]	[0.837]	[0.303]	[<0.001]	[<0.001]	[<0.001]		(0.213)	(1.540)
Pakistan	111	2.764	7.851	8.561^{+}	26.055^{*}	26.077	0.599	0.299	—	0.338	−4.274
		[0.598]	[0.097]	[0.073]	[0.011]	[<0.001]	[0.897]	[0.861]		(1.970)	(3.336)
Philippines	111	8.004	7.159	4.414	24.388^{*}	16.172	>10,000	1764.500	—	−6.954	1.033
		[0.091]	[0.128]	[0.353]	[0.018]	[0.003]	[<0.001]	[<0.001]		(0.020)	(0.111)
Portugal	110	5.333	$26.787]^{*+}$	3.652	44.601^{*+}	15.075	12.935	2.517	—	0.643	—
		[0.255]	[<0.001]	[0.455]	[<0.001]	[0.005]	[0.005]	[0.284]		(2.810)	
Taiwan	111	2.493	2.717	10.130^{*+}	16.244	227.690	111.380	82.912	—	−9.094	3.391
		[0.646]	[0.606]	[0.038]	[0.180]	[<0.001]	[<0.001]	[<0.001]		(12.695)	(2.832)
Thailand	111	8.437	3.844	2.262	15.288	16.755	2.953	2.941	—	−1.412	−0.469
		[0.077]	[0.428]	[0.688]	[0.226]	[0.002]	[0.399]	[0.230]		(1.556)	(0.268)
Turkey	121	3.353	11.132^{*+}	4.566	22.179^{*}	136.640	>10,000	>10,000	−2.419	1.782	0.465
		[0.501]	[0.025]	[0.335]	[0.036]	[<0.001]	[<0.001]	[<0.001]	(0.182)	(0.261)	(0.205)
Venezuela	120	2.702	1.231	2.352	7.049	>10,000	>10,000	>10,000	2.659	>10,000	—
		[0.609]	[0.873]	[0.671]	[0.854]	[<0.001]	[<0.001]	[<0.001]	(0.178)	(0.000)	
Zimbabwe	111	7.526	0.388	3.898	20.532	10.045	>10,000	568.720	—	−4.927	0.149
		[0.111]	[0.983]	[0.420]	[0.058]	[0.040]	[<0.001]	[<0.001]		(0.028)	(0.229)

A number of Wald tests are presented. First, consider the Wald tests for the linear information model. The first test investigates the significance of global factors in the mean. The hypothesis that the global factors do not influence the mean ($\boldsymbol{\delta}_i = 0$) is rejected in ten of 15 cases at the 5% level of significance. Wald test II determines whether there is a significant world factor in the variance ($\boldsymbol{q}_i = 0$). This hypothesis is rejected for eight of 15 countries at the 5% level of significance and nine of 15 at the 10% level. The final Wald test focuses on the coefficients of the trade and size variables in the $v_{i,t-1}$ function. They are significantly different from zero at the 5% level for six countries and at the 10% level for seven countries, indicating time variation in the world factor dependence for these countries' variances.

For the nonlinear information model, the Wald tests focus on the restrictions implied by the factor model proposed by Engle, Ng, and Rothchild (1990, 1992) and others. In particular, Wald tests I and II test whether $\kappa_i = \xi_i$ and $\theta_{i,t-1} = \psi_{i,t-1}$, respectively. Wald test III is the joint test of these two restrictions. For the four countries for which the nonlinear model is pursued, the factor model is rejected in 11 of 12 tests. The joint test provides a rejection for every country.

The next set of diagnostics focuses on the two key assumptions of the model that (i) the country shocks are independent of the world shocks and (ii) the country shocks are independent of other country shocks.

The second column of Table 4 presents the correlations of the country residual and the world residual along with a test that the covariance is equal to zero. The correlation coefficients are generally quite small. We cannot reject the hypothesis of zero covariance in any country (the lowest p-value is 0.17 for Taiwan). In addition, a joint test (using the nine countries with the longest samples) also fails to provide evidence against the null hypothesis.

The next columns in Table 4 detail the cross-correlations of the residuals. Since there are 18 cross-correlations for each country, we report the mean, minimum and maximum of the cross-correlations. We also derive the empirical distribution for these statistics and report rejections of the null of zero correlation at the 5% level.

While the mean correlations are generally small (−4.2% to 13.2%), we can reject the hypothesis of zero correlation in 11 of 19 countries. A similar inference is found in the analysis of maximum correlations in that we can reject zero correlations in nine of 19 countries. Whereas some of the high cross-correlations may have a natural interpretation (e.g., Greece and Portugal could point to a missing European factor), others are more puzzling (e.g., Malaysia and Venezuela). To help interpret the numbers, note that the 95% quantile in the distribution of the maximum correlation of 18 cross-correlations for a country with 85 (192) observations is 0.306 (0.287).

To sum up our diagnostic tests, the specification tests suggest that very few models are rejected. The hypothesis that the world residuals are independent of the country shocks is not rejected in our data although there is some evidence that

Table 4
Testing the independence assumption

We estimate the following model:

$$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t} \ (2) \quad \varepsilon_{i,t} = v_{i,t-1}\varepsilon_{w,t} + e_{i,t} \ (3)$$

$$(\sigma^{\ell}_{i,t})^2 = c_i + \alpha_i(\sigma^{\ell}_{i,t-1})^2 + \beta_i e^2_{i,t-1} + \gamma_i S_{i,t} e^2_{i,t-1} \ (4) \quad e_{i,t} = \sigma^{\ell}_{i,t} z_{i,t} \ (5)$$

where $\mu_{i,t-1}$ is the conditional mean return. The unexpected portion of country i's return, $\varepsilon_{i,t}$, is driven by a portion due to world shocks, $\varepsilon_{w,t}$, and a purely idiosyncratic shock, $e_{i,t}$. The dependence of local shocks on world shocks is determined by $v_{i,t-1}$. The local idiosyncratic standard deviation is $\sigma^{\ell}_{i,t}$, $z_{i,t}$ is a standardized residual with zero mean and unit variance, and $S_{i,t}$ is an indicator variable that takes on the value of one when the idiosyncratic shock is negative and zero otherwise. A similar model is estimated for the world market return (denoted with w subscripts). The second column reports the correlation between the world shock, $e_{w,t}$, and the idiosyncratic shock, $e_{i,t}$. In braces are the p-values from a moments test of the assumption $\mathrm{E}[e_{w,t}e_{i,t}|\boldsymbol{I}_{t-1}] = 0$. Columns three through five report the mean, minimum, and maximum correlations of $e_{i,t}$ with $e_{j,t}$. We use the maximum number of (overlapping) data to compute these correlations. The $^+$ symbol indicates 5% rejections of the null of zero correlation according to the appropriate small sample distribution. The small sample distribution is computed based on 5,000 draws of 19 independent N(0,1) samples with the same number of observations as the countries in our sample.

	Correlations of			
	e_{it} and e_{wt}	e_{it} and e_{jt}		
Country	{p-value}	Mean	Maximum	Minimum
Argentina	−0.0332 {0.6247}	0.0178	0.4773$^+$	−0.0981
Brazil	0.0483 {0.5358}	0.0358	0.2414	−0.1386
Chile	−0.0177 {0.8251}	0.0676$^+$	0.2219	−0.0344
Colombia	0.0106 {0.9018}	0.0811$^+$	0.2778	−0.2073
Greece	0.0366 {0.6177}	0.0770$^+$	0.4673$^+$	−0.2139
India	−0.0517 {0.4587}	0.0328	0.2907$^+$	−0.2073
Jordan	0.0678 {0.4867}	0.0220	0.2188	−0.1664
Korea	0.0693 {0.3402}	−0.0246	0.0921	−0.1664
Malaysia	0.1612 {0.3454}	0.0949$^+$	0.7677$^+$	−0.2139
Mexico	0.0060 {0.9410}	0.0480$^+$	0.3428$^+$	−0.1645
Nigeria	0.1021 {0.3870}	−0.0423	0.2327	−0.3390
Pakistan	−0.0888 {0.3114}	0.0234	0.2778	−0.1036

Table 4 (continued)

	Correlations of			
	e_{it} and e_{wt}	e_{it} and e_{jt}		
Country	{p-value}	Mean	Maximum	Minimum
Philippines	−0.0525 {0.7259}	0.0551^{+}	0.2531	−0.1695
Portugal	0.0063 {0.9408}	0.0918^{+}	0.4673^{+}	−0.1914
Taiwan	0.3294 {0.1662}	0.1105^{+}	0.3844^{+}	−0.1029
Thailand	0.1140 {0.3912}	0.1211^{+}	0.3844^{+}	−0.1094
Turkey	−0.1880 {0.2113}	0.1321^{+}	0.4773^{+}	−0.1616
Venezuela	−0.0056 {0.9683}	0.0734^{+}	0.7677^{+}	−0.3390^{+}
Zimbabwe	0.0628 {0.4104}	−0.0182	0.1287	−0.1166
	χ^2			
10 countries	11.7397 {0.3029}			

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample ends in December 1992.

country shocks are correlated. Of course, it would be more desirable to jointly estimate a number of countries, but this is not feasible given the small sample sizes. While the correlation of the country shocks suggests that we should exercise some caution in interpreting our results, the absolute size of the correlations is rather small.

4.3. *The time-varying influence of world factors*

One of the hypotheses in which we are interested is the link between market integration and the influence of world information on country returns. Over our sample, 17 of 19 countries experienced at least one liberalization. We investigate whether the proportion of variance caused by world factors is different across regimes. We also investigate the behavior of conditional correlations with the world equity benchmark.

Table 5 presents the mean proportion of variance due to world factors and the average conditional correlations from the world factor model. The mean proportion of variance is provided over the entire sample and for three subperiods. The first subperiod is the post-October 1987 (post-crash) period. The second subperiod is

Table 5
Correlation and the importance of world factors

The model is

$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t}$ (2) $\varepsilon_{i,t} = v_{i,t-1}\varepsilon_{w,t} + e_{i,t}$ (3) $(\sigma'_{i,t})^2 = c_i + \alpha_i(\sigma'_{i,t-1})^2 + \beta_i e^2_{i,t-1} + \gamma_i S_{i,t} e^2_{i,t-1}$ (4) $e_{i,t} = \sigma'_{i,t} z_{i,t}$ (5)

where $\mu_{i,t-1}$ is the conditional mean return. The unexpected portion of country i's return, $\varepsilon_{i,t}$, is driven by a portion due to world shocks, $\varepsilon_{w,t}$, and a purely idiosyncratic shock, $e_{i,t}$. The dependence of local shocks on world shocks is determined by $v_{i,t-1}$. The local idiosyncratic standard deviation is $\sigma'_{i,t}$, $z_{i,t}$ is a standardized residual with zero mean and unit variance, and $S_{i,t}$ is an indicator variable that takes on the value of one when the idiosyncratic shock is negative and zero otherwise. A similar model is estimated for the world market return (denoted with w subscripts). The world market correlation in our model is given by

$\rho_{it} = v_{i,t-1}(\sigma_{w,t}/\sigma_{i,t})$ (16)

The proportion of variance due to world factors is

$VR_{i,t} = v_{i,t-1}(\sigma_{iw,t}/\sigma^2_{i,t})$ (18)

	Mean proportion of variance due to world factors, $\overline{VR}_i$				Correlation, $\bar{\rho}_{it}$, with world			
Country	Full sample	Post-crash[a]	Pre-liberal[b]	Post-liberal[c]	Full sample	Post-crash[a]	Pre-liberal[b]	Post-liberal[c]
Argentina	0.003	0.006	0.002	0.009	0.032	0.056	0.037	0.070
Brazil	0.007	0.004	0.003	0.008	0.067	0.048	0.038	0.077
Chile	0.006	0.003	0.005	0.002	0.073	0.050	0.070	0.030
Colombia	0.023	0.016	0.010	0.030	−0.006	0.045	0.009	0.146
Greece	0.014	0.020	0.029	0.020	0.098	0.140	0.167	0.138
India	0.028	0.017	0.016	0.048	0.042	−0.099	−0.082	−0.219
Jordan	0.010	0.017	0.002	0.018	0.086	0.124	0.041	0.127

Korea	0.018	0.042	0.056	0.027	0.119	0.197	0.232	0.162
Malaysia	0.236	0.251	0.259	0.234	0.446	0.453	0.491	0.429
Mexico	0.059	0.126	0.066	0.191	0.190	0.298	0.185	0.416
Nigeria	0.054	0.068	—	—	−0.006	0.016	—	—
Pakistan	0.008	0.008	0.007	0.001	0.060	0.053	0.070	−0.008
Philippines	0.181	0.198	0.146	0.101	0.356	0.367	0.275	0.262
Portugal	0.338	0.366	0.167	0.395	0.507	0.539	0.299	0.564
Taiwan	0.060	0.079	0.051	0.145	−0.129	−0.195	−0.156	−0.335
Thailand	0.025	0.061	0.003	0.077	0.029	0.220	0.005	0.269
Turkey	0.073	—	0.049	0.072	0.214	—	0.172	0.191
Venezuela	0.423	0.435	0.416	0.436	0.632	0.640	0.620	0.639
Zimbabwe	0.018	0.008	—	—	0.020	0.042	—	—

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample ends in December 1992. Indonesia had too few data to estimate any of the models.

[a]Post-crash is the period after October 1987.

[b]Pre-liberalization is the period three years before significant capital market liberalizations (see Bekaert, 1995, for dates).

[c]Post-liberalization is the period after significant capital market liberalizations.

calculated in the three years before significant capital market liberalizations. The final subperiod is chosen to follow the liberalizations.

The first column in Table 5 suggests that the average proportions of variance attributable to world factors are generally small, with 16 countries having proportions of less than 10%. The largest proportions are found in Malaysia, Portugal, and Venezuela. In 11 of the 17 countries that experienced capital market liberalization, the influence of world factors increases after the liberalization. The dates for the liberalizations are drawn from Bekaert (1995). For example, in the pre-liberalization period, the proportion of variance due to world factors in Mexico is 6.6% and after the liberalization the ratio increases to 19.1%. Both Taiwan's and Thailand's ratios more than doubled after capital market liberalizations.

The average conditional correlations with the world market portfolio are also reported in Table 5. Over the full sample, there are only five countries (Malaysia, Philippines, Portugal, Turkey, and Venezuela) that have average correlations exceeding 20%. In nine of the 17 countries that experienced a capital market liberalization, the correlations with the world increase. The Mexican correlation increases from 18.5% to 41.6%. The Thai correlation rises from 0.1% to 26.9%. This evidence suggests that in most countries, world factors become more important after capital market liberalizations. However, we are not yet in a position to test whether the changes are significant. Indeed, liberalization is a gradual process and it is unlikely that we can capture its impact by a before-and-after snapshot.

4.4. Two country studies

While space does not permit a detailed examination of every country, this section highlights two important emerging equity markets, Mexico and Thailand.

Fig. 2. Analysis of Mexico.

Panel A presents the loading, $v_{i,t-1}$, on the world shock $\varepsilon_{w,t}$ from the model:

$$r_{i,t} = \mu_{i,t-1} + \varepsilon_{i,t}, \quad \varepsilon_{i,t} = v_{i,t-1}\varepsilon_{w,t} + e_{i,t}, \quad (\sigma'_{i,t})^2 = c_i + \alpha_i(\sigma'_{i,t-1})^2 + \beta_i e^2_{i,t-1} + \gamma_i S_{i,t} e^2_{i,t-1},$$
$$e_{i,t} = \sigma'_{i,t} z_{i,t},$$

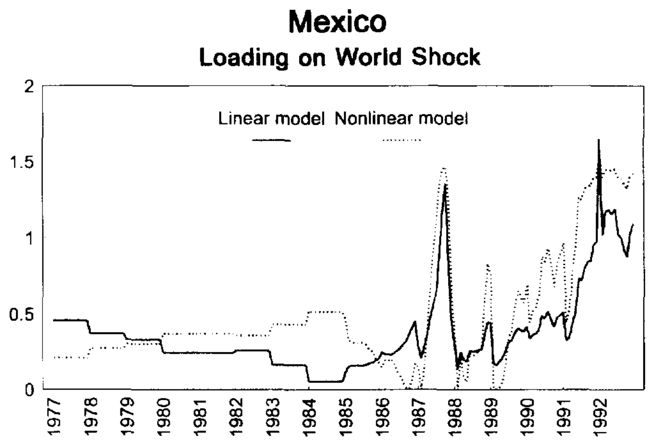
where $(\sigma'_{i,t})^2$ represents the conditional expectation of the square of the idiosyncratic country shock for Mexico, $e_{i,t}$, $\mu_{i,t-1}$ is the conditional mean, $S_{i,t}$ is an indicator variable which takes on the value of one when the unexpected mean return is negative and zero otherwise, and $z_{i,t}$ is a standardized residual with zero mean and unit variance. $\mu_{i,t-1}$ and $v_{i,t-1}$ are assumed to be linear functions of the local and global information variables in the 'linear model' and nonlinear functions in the 'nonlinear model'. Panel B presents the proportion of the Mexican variance accounted for by world factors:

$$VR_{i,t} = v^2_{i,t-1}\sigma^2_{w,t}/\sigma^2_{i,t}.$$

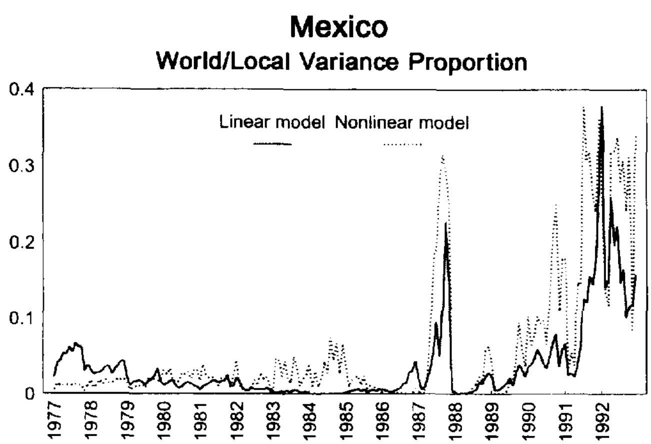
In panel C, the world market correlation is presented:

$$\rho_{it} = v_{i,t-1}(\sigma_{w,t}/\sigma_{i,t}).$$

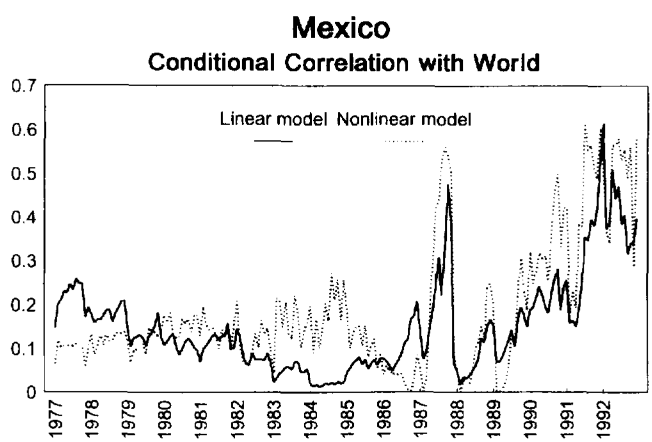
(A)


Mexico
Loading on World Shock
Linear model Nonlinear model
2
1.5
1
0.5
0
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

(B)


Mexico
World/Local Variance Proportion
Linear model Nonlinear model
0.4
0.3
0.2
0.1
0
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

(C)


Mexico
Conditional Correlation with World
Linear model Nonlinear model
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

4.4.1. Mexico

Mexico is one of the largest emerging markets, with a market capitalization of the stocks in the IFC index of \$66.1 billion in December 1992 (the last month in our sample). In June 1996, the market capitalization was \$71.0 billion. Mexico, at least prior to the devaluation of the peso in December 1994, was the emerging market most familiar to U.S. investors. This was perhaps influenced by its proximity to the U.S. or by the large number of American Depositary Receipts (36 in June 1992) and closed-end funds (six funds with capitalization of \$16 billion) available in the U.S.

We examine three measures that reflect the influence of world factors on Mexican returns: the loading on the world shock, $v_{i,t-1}$, the proportion of variance accounted for by world factors, and the conditional correlation with the world benchmark return. Fig. 2 presents these measures. Although summary statistics for the linear model are presented in Table 3, we present the three measures for both the linear and nonlinear models.

The influence of world factors sharply increases after 1988. This is most evident in the conditional correlation measure, which increases from 0% at the beginning of 1988 to over 40% by the end of the sample period. Similar patterns are evident across both the linear and nonlinear models. The nonlinear model (which is rejected in favor of the linear model) produces more volatile loadings, variance ratios, and correlations.

The increasing influence of world factors in Mexico roughly coincides with significant capital market liberalizations. E.g., after 1989, 100% foreign investment in most firms is possible. Key sector firms are restricted to 49% foreign participation and the foreign investment limit in the banking industry is 30%.

Fig. 3. Analysis of Thailand.

Panel A presents the loading, $v_{i,t-1}$, on the world shock $\varepsilon_{w,t}$ from the model:

$$r_{i,t}=\mu_{i,t-1}+\varepsilon_{i,t},\quad \varepsilon_{i,t}=v_{i,t-1}\varepsilon_{w,t}+e_{i,t},\quad (\sigma'_{i,t})^2=c_i+\alpha_i(\sigma'_{i,t-1})^2+\beta_i e_{i,t-1}^2+\gamma_i S_{i,t}e_{i,t-1}^2,$$
$$e_{i,t}=\sigma'_{i,t}z_{i,t}\,,$$

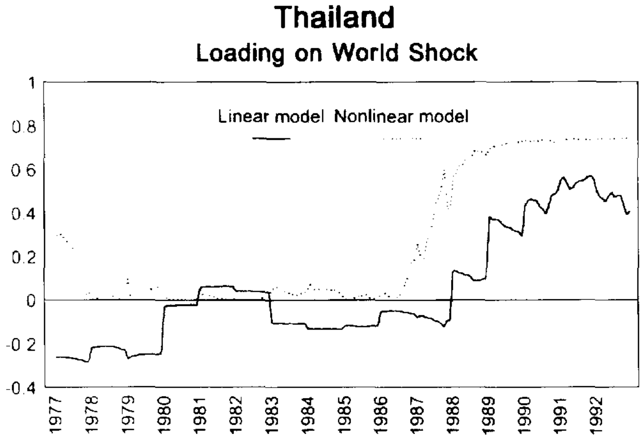
where $(\sigma'_{i,t})^2$ represents the conditional expectation of the square of the idiosyncratic country shock for Thailand, $e_{i,t}$, $\mu_{i,t-1}$ is the conditional mean, $S_{i,t}$ is an indicator variable which takes on the value of one when the unexpected mean return is negative and zero otherwise, and $z_{i,t}$ is a standardized residual with zero mean and unit variance. $\mu_{i,t-1}$ and $v_{i,t-1}$ are assumed to be linear functions of the local and global information variables in the 'linear model' and nonlinear functions in the 'nonlinear model'. Panel B presents the proportion of the Thai variance accounted for by world factors:

$$VR_{i,t}=v_{i,t-1}^2\sigma_{w,t}^2/\sigma_{i,t}^2.$$

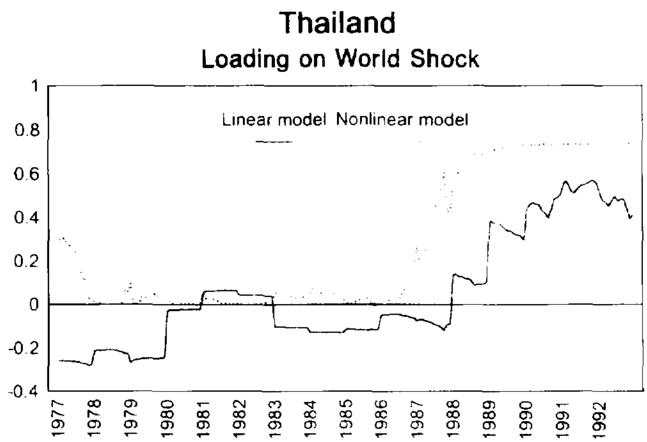
In panel C, the world market correlation is presented:

$$\rho_{it}=v_{i,t-1}(\sigma_{w,t}/\sigma_{i,t}).$$

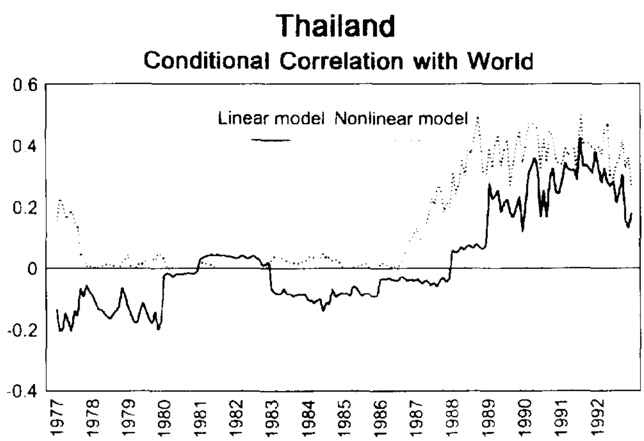
(A)


Thailand
Loading on World Shock
Linear model Nonlinear model
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

(B)


Thailand
Loading on World Shock
Linear model Nonlinear model
1
0.8
0.6
0.4
0.2
0
-0.2
-0.4
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

(C)


Thailand
Conditional Correlation with World
Linear model Nonlinear model
0.6
0.4
0.2
0
-0.2
-0.4
1977
1978
1979
1980
1981
1982
1983
1984
1985
1986
1987
1988
1989
1990
1991
1992

4.4.2. Thailand

Thailand is another large emerging market with the capitalization of the IFC index stocks being \$28.4 billion at the end of 1992. By June 1996, the market capitalization had more than tripled to \$91.1 billion. Similar to Mexico, Thailand is an emerging market that is well known to international investors.

Fig. 3 presents the loading on the world shocks, the proportion of variance explained by world factors, and the conditional correlation with the world. There are a number of similarities between the results for Mexico and Thailand. The nonlinear model is rejected in favor of the linear model, and the fitted values of the measures are much more volatile for the nonlinear model.

World factors, as in the case of Mexico, become much more important in the later part of the sample. In both 1988 and 1989, there are jumps in the loading on the world shock. In 1989, the proportion of variance accounted for by world factors increases from about 0% to close to 10%. Over the same period, the conditional correlation increases from 0% to 30%.

The increasing influence of world factors follows a number of liberalizations in the Thai market which culminate in December 1988. In particular, Bailey and Jagtiani (1994) detail the opening of the Alien Board for extranational trading of Thai securities at this time.

In recent years, world factors account for closer to 15% of the local variance. The conditional correlation with the world is close to 40% in 1991 and declines to 25% by the end of the sample. This is slightly lower than the average level of correlation that Harvey (1991) details for 17 developed market returns.

5. The cross-section of volatility in emerging markets

5.1. Explaining volatility across emerging markets

One important difference between developed and emerging capital markets is the dispersion of volatility across countries. Harvey (1993) shows that the range of unconditional volatilities in developed markets is 18% (from high to low). In emerging markets, the range is 86%. We explore four sources of volatility differences: asset concentration, stock market development/economic integration, microstructure effects, and finally macroeconomic influences and political risk. Our empirical strategy is to prespecify a set of instruments for volatility that reflect each of these categories.

5.1.1. Asset concentration

The most obvious source of volatility differences is the degree of diversification and concentration inherent in the IFC index for each country. Schwert (1989a), Harvey (1991), and Roll (1992) explore whether the number of stocks included in the index influences the cross-section of volatility. We construct a time-series of the number of stocks included in each of the IFC country indexes. Following previous research, we use the natural logarithm of the number of stocks as a proxy for the degree of diversification.

The number of stocks in the index may not be that indicative of diversification if there are a few dominant stocks and many small stocks. Roll (1992) and Harvey (1995b) examine asset concentration ratios:

$$CR_{i,t} = \sqrt{\frac{N_{i,t}}{N_{i,t}-1}\sum_{j=1}^{N_{i,t}}\left(w_{ij,t}-\frac{1}{N_{i,t}}\right)^2}, \tag{24}$$

where $N_{i,t}$ is the number of individual securities in the country i index in month t and $w_{ij,t}$ is the share of market capitalization represented by stock j at time t. If one stock dominates the index, then CR approaches one. If every stock has equal market capitalization, then $CR = 0$. Using the IFC's individual stock data, we create a time-series of concentration ratios for each country. A country index can have many stocks and a low concentration ratio but may still not be diversified if all of the stocks are involved in a single industry. Given that a time-series of industry classifications is not available, we are unable to examine the effect of industrial concentration on the cross-section of volatility.

5.1.2. Development and integration

The second source of volatility differences is linked to both the development of the stock market and the degree of market integration. Unfortunately, exact measures of stock market development and economic integration are difficult to specify. Bekaert and Harvey (1995) propose a model in which market integration is parameterized. They find that the ratio of equity capitalization to GDP is a useful instrument in characterizing the time-series of market integration. Stock market capitalization to GDP is also often used as a stock market development indicator (see Demirgüç-Kunt and Levine, 1996). We also track the size of the trade sector by forming the ratio of exports plus imports to GDP.

The way that equity returns move within a particular economy may also contain information about economic development. As an economy becomes more developed, it often becomes more diverse and, as a result, the cross-sectional volatility of the country's component stocks returns should increase. That is, as stocks are less dependent on one sector, their covariances should decrease which should increase the cross-sectional variance. At the level of the index, this effect should *decrease* market volatility. This negative relation will not necessarily hold in more developed markets.

5.1.3. *Microstructure*

The third source of volatility arises from market microstructure research. It is well known that the heterogeneity of traders' information sets as well as liquidity affects the variance of returns. We proxy for these effects by examining the role of turnover ratios in explaining the cross-section of volatility.

In developed markets, large changes in prices across securities suggest a greater flow of private information being revealed to the market. In Ross (1989), the volatility of prices is directly linked to the rate of information flow in the market. Hence, increases in the cross-sectional volatility could raise the variance of the distribution of future prices. We calculate the cross-sectional standard deviation of each index's component stock returns and the cross-sectional mean absolute deviation. These are measured each month relative to the average stock return in each country index.

5.1.4. *Macroeconomy*

The last category of volatility sources focuses on macroeconomic volatility, which Schwert (1989a,b) shows is one of the underlying forces affecting stock market volatility. Unfortunately, the macroeconomic data are sparse or nonexistent in some of the emerging markets. For instance, inflation variability is an obvious candidate for an explanatory variable. However, the data are quite difficult to obtain and, even if we used the published data, they are highly suspect in a number of countries. Since purchasing power parity is not rejected in high-inflation countries (see Liew, 1995), we use the variability of foreign exchange rate changes to proxy for inflation variability.

Political risk is also likely to influence the cross-section of volatility. However, long time-series of political risk ratings are difficult to obtain. We choose to focus on *Institutional Investor's* Country Credit Ratings. These ratings are based on a semiannual survey of bankers. *Institutional Investor* has published this survey in its March and September issues every year since 1979. The survey represents the responses of 75–100 bankers. Respondents rank each country on a scale of 0 to 100, with 100 representing the smallest risk of default. *Institutional Investor* weights these responses by its perception of each bank's level of global prominence and credit analysis sophistication (see Erb, Harvey, and Viskanta, 1994).

Credit ratings are not meant to solely represent a measure of political risk. Many macroeconomic, as well as political, factors enter the bankers' decisions on the creditworthiness of a particular country. This variable captures both political risk and macroeconomic stability. Erb, Harvey, and Viskanta (1996) show that the credit rating has high correlation with the *International Country Risk Guide*'s measures of political, economic, and financial risk. It is the only ex ante variable that we examine (in the sense that participants are asked to assess the future creditworthiness).

5.2. Methodology

The raw material for the cross-sectional analysis is the time-series estimates of conditional volatility. We estimate a pooled time-series cross-sectional regression:

$$\ln(\boldsymbol{\sigma}_i^2) = \boldsymbol{\alpha}_i + \boldsymbol{\beta}'\mathbf{X}_i + \boldsymbol{u}_i\,, \qquad i = 1,\dots,N. \tag{25}$$

There are N countries and $\boldsymbol{\sigma}_i^2$ is a $T_i \times 1$ vector of preestimated conditional variances, where T_i is the number of observations for country i, $\mathbf{X}_i$ is a matrix of L explanatory variables for country i, the $\boldsymbol{\alpha}_i$ are intercept coefficients (one for each country), and $\boldsymbol{\beta}$ is a $L \times 1$ coefficient vector. We use the conditional variance estimates from the world factor specification reported in Table 3.

This model allows for fixed effects in the cross-section by not requiring that the intercepts are identical across different countries. However, we also examine a specification in which the intercepts are constrained to be constant across countries. This allows us to test how much of the variation in volatility is explained by the specified variables. Our approach allows us to examine all observations for all countries simultaneously.

Our initial estimation technique is ordinary least squares with the standard White (1980) correction for conditional heteroskedasticity. A standard Lagrange multiplier test reveals substantial evidence against homoskedasticity across countries. (We adjust the standard test discussed in Greene, 1993, for the unequal number of observations present in our analysis.) Hence, we also present a generalized least squares estimation which allows for heteroskedasticity across countries ('group-wise heteroskedasticity'). Finally, we present estimates that correct for both group-wise heteroskedasticity and serial correlation. The serial correlation correction, detailed in Greene (1993), is specific to each country and is based on the Prais–Winsten method. This correction is particularly important given the high serial correlation in some of the countries' fitted volatility estimates.

5.3. Results

5.3.1. Summary analysis

The fitted volatility series cover (at most) January 1977 to December 1992. There are a total of 2,627 fitted variances. However, the country credit ratings only begin in March 1979. As a result, for nine countries 32 observations are lost, reducing the total number of observations to 2,339.

Some summary statistics on the variables used in the cross-sectional regressions are included in panel A of Table 6. The average values of the cross-sectional standard deviation, the number of firms in each index, the asset concentration ratio, the country credit rating, the ratio of trade to GDP, and the ratio of market capitalization to GDP are presented in this table. Correlations between the average

Table 6
Summary statistics and correlation for variances used in cross-sectional analysis

(A) *Summary statistics*

Country	Total fitted	Obs. used in regression	Mean cross-sectional Std. dev.	Mean cross-sectional Abs. dev.	Number of firms	Concentration ratio	Country credit rating	Trade/ GDP	Market capitalization/ GDP	Turnover	Foreign exchange volatility
Argentina	192	160	0.52	0.29	23.6	0.24	31.9	0.15	0.02	0.031	0.015
Brazil	192	160	0.19	0.13	31.9	0.27	37.0	0.17	0.03	0.033	0.069
Chile	192	160	0.12	0.08	25.7	0.22	37.6	0.54	0.24	0.007	0.031
Colombia	84	84	0.12	0.09	20.7	0.19	37.1	0.33	0.05	0.005	0.012
Greece	192	160	0.09	0.07	15.5	0.43	52.2	0.52	0.06	0.010	0.032
India	192	160	0.09	0.06	32.9	0.20	48.7	0.15	0.02	0.070	0.016
Indonesia	24	24	0.37	0.15	64.8	0.18	50.3	0.55	0.08	0.830	0.005
Jordan	156	156	0.07	0.05	15.3	0.56	34.4	1.19	0.30	0.012	0.019
Korea	192	160	0.09	0.07	40.7	0.18	61.6	0.69	0.12	0.076	0.012
Malaysia	84	84	0.10	0.11	53.7	0.20	59.1	1.38	0.62	0.011	0.012
Mexico	192	160	0.16	0.04	21.1	0.19	43.3	0.28	0.05	0.054	0.059
Nigeria	84	84	0.06	0.07	18.6	0.17	20.2	0.50	0.03	0.001	0.105
Pakistan	84	84	0.09	0.10	51.6	0.17	29.6	0.34	0.04	0.008	0.010
Philippines	84	84	0.13	0.08	23.1	0.33	23.7	0.57	0.11	0.021	0.022
Portugal	71	71	0.11	0.08	22.3	0.23	60.3	0.71	0.11	0.011	0.031
Taiwan	84	84	0.10	0.05	52.6	0.19	76.1	0.93	0.48	0.222	0.012
Thailand	192	160	0.07	0.11	14.1	0.33	54.1	0.58	0.06	0.043	0.014
Turkey	60	36	0.14	0.11	16.9	0.28	41.0	0.45	0.06	0.019	0.018
Venezuela	84	84	0.14	0.11	13.8	0.23	36.1	0.51	0.09	0.019	0.081
Zimbabwe	192	160	0.14	0.10	10.0	0.28	23.1	0.56	0.05	0.004	0.026

(B) *Correlations of the cross-sectional variables*

	Vol	Std. dev.	MAD	#Co	Conc	CCR	Ex+Im	Mcap	Turn	FXσ
Volatility	1.00	0.13	0.18	0.07	−0.22	−0.05	−0.38	−0.12	0.07	0.47
Standard deviation		1.00	0.99	0.02	−0.04	0.01	−0.09	−0.05	0.10	0.09
Mean absolute deviation			1.00	0.01	−0.05	−0.02	−0.12	−0.05	0.19	0.06
Number of companies				1.00	−0.58	0.21	0.02	0.40	0.23	−0.04
Concentration factor					1.00	−0.05	0.31	0.68	−0.11	−0.11
Country credit rating						1.00	0.24	0.29	0.24	−0.42
Exports+Imports/GDP							1.00	0.69	0.04	−0.37
Market capitalization/GDP								1.00	0.09	−0.23
Turnover									1.00	−0.09
Foreign exchange volatility										1.00

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample ends in December 1992. Vol is the conditional volatility estimated from the time-series models, Std. dev. is the cross-sectional standard deviation of the individual stock returns in each country's index, MAD is the cross-sectional mean absolute deviation of the individual stock returns, #Co is the number of companies in the IFC index, Conc is the asset concentration ratio, Cred is country credit rating, Ex+Im is exports plus imports divided by GDP, Mcap is market capitalization divided by GDP, Turn is turnover (value of trading divided by market capitalization), and FXσ is the volatility of the previous three years' exchange rate changes.

volatilities and these variables are presented in panel B. None of the variables are extremely correlated except for the two measures of cross-sectional volatility (these two measures are never included together in a regression).

5.3.2. Time-series cross-sectional analysis

The time-series cross-sectional regression results are presented in Table 7. Panel A considers the estimation with the standard White (1980) correction for heteroskedasticity. The results that correct for group-wise heteroskedasticity are presented in panel B and the estimation that corrects for both group-wise heteroskedasticity and serial correlation is in panel C.

In the base case with no country-specific intercepts, 27% of the cross-section of volatility is explained with the eight variables. Separate regressions are run with the cross-sectional standard deviation of the individual index stocks and the cross-sectional mean absolute deviation because these measures are 99% correlated. When the country-specific intercepts are included, the explanatory power of the regressions increases to 54%.

The way the cross-sectional standard deviation affects volatility depends on the level of market development. Hence, we allow this variable to enter the regression as an interaction variable associated with the deviation from the cross-sectional mean ratio of market capitalization to GDP. If $MC_t^i/GDP_t < \overline{(MC_t/GDP_t)}$, which is always true for Zimbabwe, for example, then an increased cross-sectional standard deviation negatively affects the market volatility. If $MC_t^i/GDP_t > \overline{(MC_t/GDP_t)}$, then the derivative of volatility with respect to the cross-sectional standard deviation is positive, as predicted by the information flow model of Ross (1989). The results provide some support for this specification. Both the cross-sectional standard deviation and the interaction term enter the regression with coefficients that are more than two standard errors from zero in panels A and B. The coefficients are positive for the regression with standard deviations in panel C but are less significant.

The number of companies in the index rarely plays an important role in the estimations. The concentration factor produces some puzzling results. In the regressions without fixed effects, the coefficient is positive or not significant (implying more concentration associated with higher volatility). However, in the regressions with country dummy variables, the concentration factor is weakly negatively related to volatility, although in panel C the coefficient is never more than two standard errors below zero.

Some caution must be exercised in interpreting the relation between turnover and volatility. There are two countries, Taiwan and Korea, with turnover ratios of an order of magnitude greater than the other countries. In the regressions without fixed effects, there is a positive relation between turnover and volatility. In the regressions with country indicators, the significance disappears. Since the turnover data begin in 1986, a separate regression is estimated with turnover included and the coefficients are reported in the far right column of panel A of Table 7.

Table 7
Explaining the cross-section of variance

Fixed effects	Xvol	Xvol*	#Co	Conc	CCR	Ex+Im	Mcap	FXσ	Liberalization indicators: Before	Pre-	Mid-	Post-	χ^2	R^2	Turn
(A) White standard errors															
No	0.395[a]	4.406[a]	0.158	0.711	0.011	−1.223	0.215	9.797						0.272	1.660
	(0.109)	(1.356)	(0.061)	(0.252)	(0.002)	(0.126)	(0.238)	(0.575)							(0.998)
No	1.007	8.662	0.181	0.765	0.011	−1.175	−0.005	9.770						0.278	1.140
	(0.322)	(2.514)	(0.062)	(0.249)	(0.002)	(0.127)	(0.264)	(0.584)							(0.961)
Yes	0.200[a]	3.059[a]	0.060	−1.957	−0.005	−0.402	−0.519	3.105						0.537	−0.029
	(0.072)	(1.331)	(0.071)	(0.249)	(0.002)	(0.293)	(0.281)	(0.634)							(0.861)
Yes	0.519	6.718	0.095	−1.906	−0.005	−0.354	−0.719	3.246						0.539	−0.371
	(0.171)	(2.503)	(0.071)	(0.250)	(0.002)	(0.293)	(0.295)	(0.635)							(0.839)
Yes	0.319	2.530	−0.032	−2.115	−0.005	−0.569		2.937						0.537	−0.351
	(0.167)	(2.369)	(0.055)	(0.224)	(0.002)	(0.257)		(0.632)							(0.842)
Yes	0.540	7.152	0.100	−1.833	−0.004		−0.832	3.433						0.538	−0.592
	(0.170)	(2.508)	(0.071)	(0.236)	(0.002)		(0.257)	(0.632)							(0.842)
No	0.435[a]	5.167[a]	0.126	0.648	0.011	−1.199	0.076	9.828	0.048	0.235	0.247	0.097	3.119	0.276	
	(0.114)	(1.491)	(0.071)	(0.257)	(0.002)	(0.124)	(0.253)	(0.596)	(0.112)	(0.125)	(0.139)	(0.126)	[0.077]		
No	1.121	10.983	0.149	0.707	0.011	−1.160	−0.259	9.818	0.025	0.233	0.262	0.116	2.236	0.282	
	(0.325)	(2.844)	(0.071)	(0.255)	(0.002)	(0.125)	(0.289)	(0.603)	(0.112)	(0.124)	(0.140)	(0.126)	[0.135]		

Table 7 (continued)

Fixed effects	Xvol	Xvol*	#Co	Conc	CCR	Ex + Im	Mcap	FXσ	Liberalization indicators: Before	Pre-	Mid-	Post-	χ^2
(B) *Group-wise heteroskedasticity*													
No	0.347[a]	3.062[a]	0.158	−0.146	0.006	−0.744	−0.509	9.909					
	(0.066)	(1.026)	(0.038)	(0.204)	(0.001)	(0.069)	(0.136)	(0.499)					
No	0.916	5.259	0.169	−0.095	0.005	−0.708	−0.603	9.812					
	(0.127)	(1.658)	(0.038)	(0.204)	(0.001)	(0.069)	(0.149)	(0.500)					
Yes	0.048[a]	0.796[a]	0.203	−2.174	0.002	0.188	−0.800	1.504					
	(0.034)	(0.650)	(0.039)	(0.165)	(0.001)	(0.132)	(0.128)	(0.260)					
Yes	0.154	2.205	0.213	−2.173	0.002	0.225	−0.880	1.596					
	(0.065)	(1.157)	(0.040)	(0.166)	(0.001)	(0.132)	(0.138)	(0.269)					
Yes	−0.033	−1.739	0.058	−2.473	0.001	−0.129		1.311					
	(0.058)	(0.966)	(0.031)	(0.157)	(0.001)	(0.125)		(0.259)					
Yes	0.149	2.062	0.206	−2.192	0.001		−0.783	1.469					
	(0.065)	(1.139)	(0.039)	(0.164)	(0.001)		(0.125)	(0.259)					
No	0.358[a]	3.292[a]	0.159	−0.190	0.007	−0.776	−0.552	10.021	−0.131	0.030	−0.204	−0.081	5.016
	(0.069)	(1.102)	(0.044)	(0.212)	(0.001)	(0.070)	(0.155)	(0.505)	(0.069)	(0.076)	(0.088)	(0.082)	[0.025]
No	0.935	5.723	0.172	−0.142	0.007	−0.732	−0.670	9.952	−0.139	0.028	−0.201	−0.080	4.767
	(0.131)	(1.824)	(0.044)	(0.210)	(0.001)	(0.070)	(0.174)	(0.508)	(0.069)	(0.075)	(0.087)	(0.081)	[0.029]

(C) *Serial correlation and group-wise heteroskedasticity*

No	0.017[a]	0.360[a]	0.026	0.080	0.002	−0.786	−0.032	4.057					
	(0.017)	(0.322)	(0.062)	(0.240)	(0.002)	(0.142)	(0.148)	(0.648)					
No	0.020	0.470	0.031	0.045	0.003	−0.927	−0.031	5.399					
	(0.036)	(0.585)	(0.063)	(0.248)	(0.002)	(0.140)	(0.159)	(0.633)					
Yes	0.013	0.331	−0.011	−0.185	0.000	0.205	−0.023	0.658					
	(0.015)	(0.273)	(0.053)	(0.181)	(0.002)	(0.171)	(0.131)	(0.369)					
Yes	0.014	0.557	−0.009	−0.202	0.000	0.227	−0.049	0.612					
	(0.028)	(0.461)	(0.054)	(0.182)	(0.002)	(0.172)	(0.138)	(0.341)					
Yes	0.010	0.475	−0.015	−0.197	−0.000	0.224		0.582					
	(0.026)	(0.418)	(0.051)	(0.178)	(0.002)	(0.172)		(0.332)					
Yes	0.013	0.538	0.001	−0.223	0.000		−0.026	0.608					
	(0.028)	(0.462)	(0.053)	(0.182)	(0.002)		(0.172)	(0.332)					
No	0.017[a]	0.355[a]	0.029	0.032	0.002	−0.836	−0.004	4.372	0.140	0.140	0.098	0.055	2.651
	(0.018)	(0.326)	(0.064)	(0.246)	(0.002)	(0.141)	(0.149)	(0.660)	(0.307)	(0.308)	(0.309)	(0.310)	[0.104]
No	0.020	0.453	0.036	−0.008	0.003	−0.972	0.003	5.612	0.179	0.180	0.129	0.081	3.336
	(0.036)	(0.593)	(0.065)	(0.252)	(0.002)	(0.138)	(0.157)	(0.636)	(0.294)	(0.295)	(0.296)	(0.298)	[0.068]

All monthly returns are from International Finance Corporation and calculated in U.S. dollars. The sample ends in December 1992. Fixed effects means that there is a different intercept for each country. Xvol is the cross-sectional standard deviation of the individual stock returns in each country's index (denoted with an [a]) or the mean absolute deviation, Xvol* is the cross-sectional standard deviation multiplied by the deviation from the cross-sectional average market capitalization (denoted with an [a]) or the equivalent measure based on mean absolute deviation, #Co is the number of companies in the IFC index, Conc is the asset concentration ratio, Cred is country credit rating, Ex+Im is exports plus imports divided by GDP, Mcap is market capitalization divided by GDP, Turn is turnover (value of trading divided by market capitalization), and FXσ is the volatility of the previous three years' exchange rate changes. Before represents more than 30 months before liberalization, pre-liberalization is the period 30 to six months prior to liberalization, mid-liberalization is six months prior to three months after liberalization, and post-liberalization is four months after liberalization to the end of the sample period.

The Wald test of whether volatility is different is conducted on the indicators for pre-liberalization and post-liberalization. The χ^2 statistic has one degree of freedom.

The country credit rating enters with inconsistent coefficients across the different specifications. The negative coefficients in panel A suggest that a lower credit rating is associated with higher volatility. However, the coefficient in other panels is often positive.

There is a very significant negative relation between the size of the trade sector and volatility. In the regression without country-specific dummy variables, the coefficients on the trade variables are often five to ten standard errors from zero irrespective of the standard error correction. A more open economy is associated with lower volatility.

The ratio of market capitalization to GDP generally enters the regression with a negative sign in panels A and B (larger equity market implies lower volatility). This result persists when the regression is run without the trade variable, which has a 70% correlation with market capitalization. However, in the estimation that corrects for serial correlation and heteroskedasticity, this variable no longer enters with a coefficient significantly different from zero.

Finally, the volatility of changes in foreign exchange rates plays a very important role in explaining equity return volatility. In the regression without fixed effects, the coefficient on this variable is often more than nine standard errors from zero. When this variable is removed from the regression, the adjusted R-square drops from 27.2% to 16.8%. When country dummy variables are allowed, the coefficient is six standard errors from zero. The significance of this variable is not that surprising given that we are measuring equity returns in U.S. dollars. As an additional diagnostic, we replicate panel C with the alternative volatility model (the one that did not win in the R-square test). The results are broadly similar.

5.4. Capital market liberalization and volatility

Fig. 4 informally characterizes the effect of capital market reforms on variance. The average conditional variance two years after the reform (major liberalization dates are from Bekaert, 1995) is depicted on the y-axis and the average conditional variance two years before the reform is presented on the x-axis. On average, if there is no effect on volatility the variances should fall on or close to the 45° line. If variance decreases, then many of the points should fall below this line.

The evidence in Fig. 4 suggests that volatility decreases in many countries after liberalizations. Of the 17 countries that underwent a liberalization in our sample, most are near or below the 45° line. The one exception is Pakistan, whose conditional volatility has been much greater after liberalization. Particularly dramatic decreases in conditional volatility are found for Brazil, Mexico, Taiwan, and Portugal.

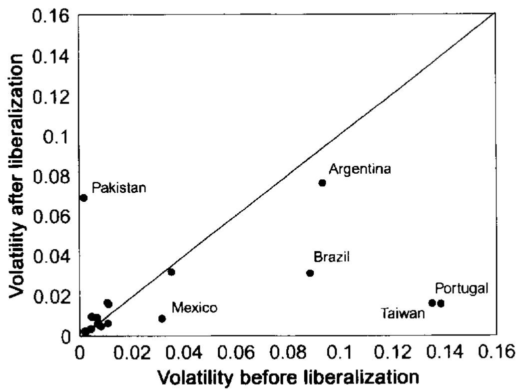


Fig. 4. Capital market liberalizations and volatility.

Average conditional variance from the world factor model is presented two years before (x-axis) and two years after (y-axis) capital market liberalizations. Countries that fall below the 45° line indicate volatility decreases after liberalizations.

A weakness of this analysis is that other events could occur that decrease or increase volatility but have little to do with capital market liberalizations. Therefore, we introduce liberalization dummy variables into our cross-sectional analysis and test whether, after controlling for these factors, these interventions significantly decrease volatility. The results are in last two rows of panels A through C of Table 7. We introduce four dummy variables to break each of the 17 countries' volatility into four pieces: before (more than 30 months before liberalization), pre- (30 to six months prior to liberalization), mid- (six months prior to three months after liberalization), and post- (four months after liberalization to the end of the sample period). The logic here is that when liberalizations are pre-announced or anticipated by market participants, volatility may change some time before the liberalization date.

The results are striking. For every specification in panels A through C, the post-liberalization coefficients are lower than the pre-liberalization coefficients. We also report heteroskedasticity-consistent Wald tests on these coefficients. There is marginal evidence that the decrease in volatility is statistically significant for most specifications and strong evidence in the estimations that correct for group-wise heteroskedasticity.

6. Conclusions

Volatility is a key input for the cost of capital calculation for a segmented market and is critical for effective asset allocation decisions. The goal of our paper is to broaden our understanding of the behavior of volatility in emerging equity markets.

For the set of markets that we study, there is little to be learned from implementing off-the-shelf univariate volatility models. Our focus is on the forces that determine volatility. In fully integrated markets, volatility is strongly influenced by world factors. In segmented capital markets, volatility is more likely to be influenced by local factors. Our decomposition of the sources of variation in volatility sheds light on how each market is affected by world capital markets and on how this impact varies over time.

We also explore the forces that determine why volatility is different in the various emerging markets. We construct variables that proxy for asset concentration, the stage of stock market development, microstructure effects, macroeconomic influences, and political risk. Among other interesting findings, we show that more open economies (in terms of world trade) have significantly lower volatilities.

Finally, we study the effect of capital market liberalizations on volatility. Our evidence suggests that volatility decreases in most countries that experience a liberalization. There is a sharp drop in volatility in five countries in our sample. Even after controlling for all of the potential influences on the time-series and cross-section of volatility, we find that capital market liberalizations significantly decrease volatility in emerging markets.

To put our results in perspective, consider the following experiment with a poorly developed stock market in a relatively closed country. Such a market is likely to be characterized by high stock market volatility, a low cross-sectional standard deviation, a high concentration ratio, and a low ratio of market capitalization to GDP. There may be political risk reflected in a low credit rating, and unstable macroeconomic policies translating into high foreign exchange volatility. We interpret high (low) as the top (bottom) quartile in the cross-sectional distribution of the relevant variables using all of the observations for all of the countries over the full sample period. Our regression analysis suggests that if the country experiences a liberalization and moves from the 25% quartile to the median, volatility decreases by more than 6% (e.g., from 30% to 24%) using our most general econometric model (see Fig. 5). This result is robust across our different estimation techniques. A decrease in volatility of this magnitude can have an important effect on the cost of capital in an emerging market.

Appendix A: The likelihood function for the world factor model

In this appendix, we construct the joint likelihood function for all the data used in estimating the GARCH models described in (2)–(5). We then discuss the necessary assumptions to make it collapse to the 21 univariate likelihoods maximized in this article.

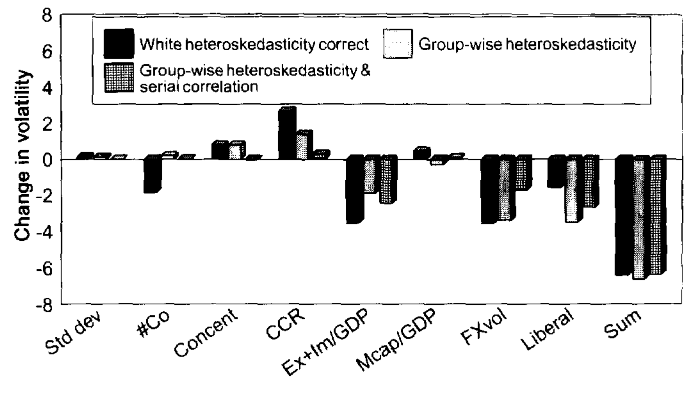


Fig. 5. The economic impact on volatility of a hypothetical country moving from the 25th percentile to the median.

The country begins with low cross-sectional standard deviation of individual stock returns (Std. dev.), a small number of securities included in the index (#Co), a high concentration ratio (Concent), low ratio of equity market capitalization to GDP (Mcap/GDP), low credit rating (CCR), high foreign exchange volatility (FXvol), and a small trade sector (Ex+Im/GDP). The country then experiences a capital market liberalization (Liberal) which brings it from the 25th (or 75th) percentile to the median of the cross-sectional distribution of all variables. The bars represent the marginal effect of each variable. Sum represents the cumulative effect of all variables. The bars represents the effects implied by three different econometric models: White (1980) heteroskedasticity correction, group-wise heteroskedasticity, and group-wise heteroskedasticity plus serial correlation correction.

We start by introducing some notation. Let $\boldsymbol{r}_t = [r_{w,t}, r_{1,t}, r_{2,t}, \ldots, r_{N,t}]'$ and $\boldsymbol{r}_{e,t} = [r_{1,t}, r_{2,t}, \ldots, r_{N,t}]'$, that is, $\boldsymbol{r}_{e,t}$ represents the emerging market returns only. Let $\boldsymbol{Z}_t = [\mathbf{X}_t', \mathbf{X}_{1,t}', \ldots, \mathbf{X}_{N,t}']'$ where $\mathbf{X}_{i,t}$ includes all the information variables used in the estimation of the emerging market returns models, including $\mathbf{X}_{i,t}^*$. Our information set, $\boldsymbol{I}_{t-1}$, then consists of the collection of data $\{\boldsymbol{q}_{t-1}, \boldsymbol{q}_{t-2}, \ldots, \boldsymbol{q}_1, \boldsymbol{q}_0\}$ with $\boldsymbol{q}_t = [\boldsymbol{r}_t', \boldsymbol{Z}_t']'$. The collection of all of our data can be described by $\tilde{\boldsymbol{q}}_T = [\boldsymbol{q}_T', \boldsymbol{q}_{T-1}', \ldots, \boldsymbol{q}_1', \boldsymbol{q}_0']'$. Analogous definitions apply to $\tilde{\boldsymbol{r}}_T$ and $\tilde{\boldsymbol{Z}}_T$. Note that we will always condition on an initial observation vector, $\boldsymbol{q}_0$. The parameters of the likelihood function are denoted by $\boldsymbol{\theta}$. We seek to maximize $f(\tilde{\boldsymbol{q}}_T; \boldsymbol{\theta})$ over $\boldsymbol{\theta}$, where $f(\cdot)$ represents a density function, which need not be normal.

Using conditioning arguments, it follows that

$$
\begin{aligned}
f(\tilde{\boldsymbol{q}}_T; \boldsymbol{\theta}) &= \prod_{t=1}^{T} f(\boldsymbol{q}_t | \boldsymbol{I}_{t-1}; \boldsymbol{\theta}) \\
&= \prod_{t=1}^{T} f(\boldsymbol{Z}_t | \boldsymbol{r}_t, \boldsymbol{I}_{t-1}; \boldsymbol{\theta}) \times f(\boldsymbol{r}_t | \boldsymbol{I}_{t-1}; \boldsymbol{\theta}).
\end{aligned}
$$

Maximizing $f(\tilde{\boldsymbol{q}}_T;\boldsymbol{\theta})$ would amount to full information maximum likelihood which is infeasible given the dimension of $\boldsymbol{q}_t$. Instead, we parameterize the model such that $\boldsymbol{\theta} = [\boldsymbol{\theta}_a', \boldsymbol{\theta}_b']'$, $f(\boldsymbol{Z}_t|\boldsymbol{r}_t, \boldsymbol{I}_{t-1};\boldsymbol{\theta}_a)$ and $f(\boldsymbol{r}_t|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b)$, where $\boldsymbol{\theta}_a$ and $\boldsymbol{\theta}_b$ have no overlapping parameters. In particular, $\boldsymbol{\theta}_b = [\boldsymbol{\theta}_w', \boldsymbol{\theta}_1', \ldots, \boldsymbol{\theta}_N']'$ with $\boldsymbol{\theta}_w = [\boldsymbol{\delta}_w', c_w, \alpha_w, \beta_w, \gamma_w]'$, $\boldsymbol{\theta}_i = [\boldsymbol{\delta}_i', c_i, \alpha_i, \beta_i, \kappa_i, \gamma_i, \xi_i, \zeta_i, \boldsymbol{\lambda}_i', \boldsymbol{\xi}_i']'$ for all i. Note that without loss of generality, we focus on the estimation of the nonlinear model. We parameterize the model such that $f(\boldsymbol{r}_t|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b)$ is a well-defined density that allows identification of $\boldsymbol{\theta}_b$. Ignoring the information in $f(\boldsymbol{Z}_t|\boldsymbol{r}_t, \boldsymbol{I}_{t-1};\boldsymbol{\theta}_a)$ means that our estimation yields consistent but inefficient estimates, relative to full information maximum likelihood.

We further simplify the problem as follows:

$$
\begin{aligned}
f(\boldsymbol{r}_t|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b) &= f(\boldsymbol{r}_{e,t}, \boldsymbol{r}_{w,t}|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b) \\
&= f(\boldsymbol{r}_{e,t}|\boldsymbol{r}_{w,t}, \boldsymbol{I}_{t-1};\boldsymbol{\theta}_b) \times f(\boldsymbol{r}_{w,t}|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b)\,.
\end{aligned}
$$

Since $f(\boldsymbol{r}_{w,t}|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_b)$ in our parameterization only depends on $\boldsymbol{\theta}_w$, we can obtain consistent estimates of $\boldsymbol{\theta}_w$ by maximizing the well-defined density $f(\boldsymbol{r}_{w,t}|\boldsymbol{I}_{t-1};\boldsymbol{\theta}_w)$. Again we sacrifice some efficiency, but this approach allows us to use the full sample on world market return data to estimate $\boldsymbol{\theta}_w$.

Consider the remaining piece of the likelihood function, $f(\boldsymbol{r}_{e,t}|\boldsymbol{r}_{w,t}, \boldsymbol{I}_{t-1};\boldsymbol{\theta}_b)$, and define $\boldsymbol{\theta}_e = [\boldsymbol{\theta}_1', \ldots, \boldsymbol{\theta}_N']'$, $\boldsymbol{e}_{e,t} = [e_{1,t}, \ldots, e_{N,t}]'$, and $\boldsymbol{\varepsilon}_{e,t} = [\varepsilon_{1,t}, \ldots, \varepsilon_{N,t}]'$. Our parameterization is such that $\boldsymbol{\theta}_b = [\boldsymbol{\theta}_w', \boldsymbol{\theta}_e']'$. We will maximize this piece of the likelihood conditional on $\hat{\boldsymbol{\theta}}_w$ and $\hat{\varepsilon}_{w,t}$; in doing so, we will not correct for the sampling error incurred in estimating $\hat{\boldsymbol{\theta}}_w$.

It turns out that with the model specified in Section 2.1, the likelihood function simplifies further:

$$
\begin{aligned}
f(\boldsymbol{r}_{e,t}|\boldsymbol{r}_{w,t}, \boldsymbol{I}_{t-1};\hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_e) &= f(\boldsymbol{\varepsilon}_{e,t}|\hat{\varepsilon}_{w,t}, \boldsymbol{I}_{t-1};\hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_e) \\
&= f(\boldsymbol{e}_{e,t}|\hat{\varepsilon}_{w,t}, \boldsymbol{I}_{t-1};\hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_e) \\
&= \prod_{i=1}^{N} f(e_{i,t}|\hat{\varepsilon}_{w,t}, \boldsymbol{I}_{t-1};\hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_e) \\
&= \prod_{i=1}^{N} f(e_{i,t}|\hat{\varepsilon}_{w,t}, \boldsymbol{I}_{t-1};\hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_i)\,.
\end{aligned}
$$

The first step follows from the definition of the information set; the second step from the definition of $\varepsilon_{i,t}$ and the fact that we condition on $\hat{\varepsilon}_{w,t}$; the third step follows from assumptions (6) and (7) in the case of a normal density but requires the idiosyncratic shocks to be independent when we use the t and SPARCH distributions; and the fourth step follows from our particular parameterization of the emerging market models. Hence, to identify $\boldsymbol{\theta}_i$ for all i, we maximize N different univariate likelihoods,

$$\sum_{t=1}^{T_i} \log f(e_{i,t}|\hat{\varepsilon}_{w,t}, \boldsymbol{I}_{t-1}; \hat{\boldsymbol{\theta}}_w, \boldsymbol{\theta}_i),$$

where T_i is the number of observations for country i. Again, there is loss of efficiency, but we can use all of the available data for each individual country.

Appendix B: Empirical distribution of specification test statistics

The statistics proposed in the paper to test whether our models are well-specified are asymptotically distributed as $\chi^2(4)$ for the mean, moments, and variance test and $\chi^2(12)$ for the joint test. There are two main reasons that the actual distributions may differ substantially from the asymptotic ones. First, the derivation of the asymptotic distribution is not strictly valid in the case of scaled residuals, which depend on pre-estimated parameters and a number of predetermined variables. Second, we use relatively small samples in our empirical work.

To get a better idea of the actual empirical distribution of the specification test statistics, we conduct a number of Monte Carlo experiments. In Table A.1 (panel A), we report the results for the tests that use an Andrews (1991) type serial correlation correction. The first experiment reconstructs returns according to the world market model with normal innovations and no asymmetry. That is, we draw normal residuals with the conditional variance determined by the estimated GARCH model, and reconstruct the returns assuming the predetermined variables to be fixed. This can be done for the same number of observations (262) as used in the estimation of the world market return model. We conduct similar experiments using 192 and 85 observations to correspond to samples that are frequently used in our empirical work on the emerging markets. To do so, we reestimate the world market return model using the most recent 192, resp. 85 observations and use these parameters to reconstruct returns in the Monte Carlo experiments. Once a series of returns is reconstructed, we simply reestimate the GARCH model as described in the paper. Hence, these experiments yield a small-sample distribution that also reflects the effect of the scaled residuals being pre-estimated, although not the effect of the instruments being dynamic variables.

The second experiment is carried out to distinguish the effects of pre-estimation from pure small-sample effects on the empirical distribution. Here, we simply draw standard random normals and conduct the specification tests for various sample sizes. To illustrate the convergence to the asymptotic distribution, we conduct these experiments for sample sizes of 10,000 and 1,000 observations in addition to the samples of 262, 192, and 85 observations.

Table A.1
Empirical critical values for specification test statistics

Critical values for a 5% size test are reported. In panel A the tests use a serial correlation correction due to Andrews (1991), whereas in panel B no serial correlation correction is made. For the critical values on the first line, return samples are reconstructed according to the estimated model for the world market return with normal innovations but without asymmetry and assuming the instruments to be fixed regressors. A univariate GARCH model is then estimated for each sample, the scaled residuals reconstructed, and the test statistics recorded. The critical values on the second line simply use the empirical distribution resulting from applying the tests on samples of N(0,1) variables. We conduct 1,500 experiments, but in the case of the estimated scaled residuals, some experiments had to be discarded because the estimation gave rise to a nonstationary conditional variance process.

(A) *Andrews (1991) serial correlation correction*

	Sample size					
Test	∞	10,000	1,000	262	192	85
Mean	—	—	—	9.91	10.51	11.68
	{9.49}	{9.31}	{9.71}	{9.62}	{9.82}	{10.48}
Moments	—	—	—	17.32	21.08	40.05
	{9.49}	{9.52}	{13.86}	{24.98}	{32.39}	{76.23}
Variance	—	—	—	8.07	7.72	7.86
	{9.49}	{9.55}	{9.80}	{9.93}	{10.04}	{10.46}
Joint	—	—	—	34.21	40.63	81.67
	{21.00}	{22.03}	{29.84}	{51.26}	{63.10}	{166.58}

(B) *No serial correlation correction*

	Sample size					
Test	∞	10,000	1,000	262	192	85
Mean	—	—	—	9.54	9.78	9.89
	{9.49}	{9.33}	{9.37}	{9.14}	{9.55}	{9.19}
Moments	—	—	—	16.14	18.94	27.09
	{9.49}	{9.51}	{13.68}	{22.88}	{27.06}	{39.42}
Variance	—	—	—	8.07	7.55	6.92
	{9.49}	{9.54}	{10.00}	{9.77}	{9.88}	{8.85}
Joint	—	—	—	29.71	33.35	41.03
	{21.00}	{21.99}	{28.91}	{41.18}	{45.90}	{51.70}

The means and variance tests on the scaled residuals test the restrictions implied by the three distributional assumptions: normal, t-distribution, and mixture of normals (SPARCH); see Eqs. (19) and (20). The means test is based on the first four autocovariances of the scaled residuals (21c); the variance test is based on the first four autocovariances of the squared scaled residuals (21f); the moments tests is based on four moments (mean, variance, skewness, and kurtosis (21a,b,d,e); and the joint test is based on all the restrictions.

In Table A.1 (panel A), we report the results for the tests that use an Andrews (1991) type serial correlation correction. The results are striking. Looking at the second lines in Table A.1, it becomes clear that convergence to the asymptotic distribution is quite slow and that for the samples we use, asymptotic tests would over-reject. This rightward shift in the distribution is especially severe for the moments test, which reflects the difficulty in estimating higher-order moments with small sample sizes. Whereas estimating the residuals makes the rightward shift in the 5% critical values slightly worse for the mean test, it reduces it for the moments test and the variance test. In fact, for the variance test the small-sample critical values are below the asymptotic ones. When judging the performance of our model, we used the first line critical values.

The small-sample distribution may be affected by the underlying model. We conduct the same experiment using normal innovations but with asymmetric GARCH. The critical values are not substantially different from those reported in Table A.1.

Finally, the serial correlation correction could lead to additional small-sample biases, and we also record the test statistic values for the tests that impose the zero serial correlation restriction. Panel B shows that the small-sample biases are indeed smaller for the version of the tests without the serial correlation correction, except for the variance test. Without knowing the power properties of the tests, it is difficult to choose between the two versions, but we report the test without the serial correlation correction.

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