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Volatility Characteristics and Persistence in Latin American Emerging Markets

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This paper examines the effects of world market volatility on the systematic risk and volatility in four emerging Latin American markets: Argentina, Brazil, Chile, and Mexico. We choose this sample of emerging markets because of their varying capitalization and investor composition. Employing a TARCH (1,1) model, our findings show that the markets under study show high volatility persistence relative to the world market. However, returns and systematic risk in these Latin American emerging markets are found to be independent of the world market. Granger tests of causality verify that the volatility in these emerging markets is independent of the world market volatility and vise versa. Therefore, investors may reduce risk by including Latin equities or index funds in their portfolios.

I. INTRODUCTION

There is general agreement that investors, within a given time period, require a larger expected return from securities that are riskier. However, the relation between risk and return across time is uncertain and has been the focus of much research in recent years. The ability to properly model time-varying volatility has attracted interest of academic researchers, portfolio managers, governmental agencies and individual investors for such reasons as establishing circuit breakers in the market, international portfolio diversification, and option pricing and valuation.

Because of this interest, a large body of research addresses the time-varying and persistent stock market volatility in the United States (US) (see Attanasio [2], Baillie and DeGennaro [4], Schwert and Seguin [30], among others), international markets (see Booth et al. [10], Poon and Taylor [28], Koutmos et al. [21], among others), and its international transmission (Hamao, et al. [16], King and Wadhwani [20], and Susmel an Engle [32], among others). The explanations given for market volatility are continuous flow of uneven information cited by Gallant et al. [14], nominal interest rates and dividend yield by Attanasio and Wadhwani [3], and margin requirements by Hardouvelis

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[17]. A brief summary of some of these papers and highlights of their findings follows.

Poon and Taylor investigate the relationship between stock returns and volatility in the UK using daily, weekly, fortnightly, and monthly returns on the Financial Times All Share Index from January 1965 to December 1989. Volatility estimates are obtained from monthly sample variances and autoregressive conditional heteroskedasticity models (ARCH). Expected returns are shown to have had a positive, though not statistically significant, relationship with expected time varying volatility.

Hamao et al. [16] investigate the time varying volatility of stock prices in several markets, employing GARCH model and document volatility spillover among stock markets of US, UK, and Japan. For close-to-open returns, their findings are consistent with international financial integration.

Koutmos et al. [21] test time-varying behavior and volatility persistence in ten major industrialized markets. They apply a moving average generalized autoregressive conditional heteroskedasticity (MA-GARCH) model to estimate the volatility persistence and the half-life of volatility in these markets. Then, applying Schwert and Seguin [30] method, they estimate the time-varying beta in these markets. Their findings show that the higher the systematic risk, the longer the volatility persistence during periods of volatile world market.

The increasing globalization of financial markets and possibility of diversification across many markets necessitate further research on issues of market volatility and its spillover internationally. Global volatility is of special interest because recent data show that venturing into emerging markets is often perilous. For example, the second half of 1997 witnessed a roller coaster ride for most investors in emerging markets as regional risks spread from market to market, eliminating most of the stellar gains of the prior year.[1]

Volatility of emerging markets has become a concern for U.S. and other investors and money managers for several reasons. First, globalized portfolios necessarily may not possess less risk. For example, if volatility in emerging markets is persistent and spills over from them to other world markets, then diversification benefits may be minimal during the periods of high volatility, when diversification is purportedly most beneficial. Second, volatile markets may lose investor confidence, impeding local firms' ability to raise capital, and stunting future growth in these economies. The long-run effect may be a loss of profitable markets for the U.S. firms, adversely affecting the U.S. security prices.

Thirdly, the results of this paper may also be informative to international financial organizations such as IMF. The spillover of volatility in the financial markets may create a liquidity crunch in other markets, forcing financial institutions and banks to sell at the bottom of the security price cycle, exacerbating global market volatility and causing further liquidity crunch. Events of the second half of 1997 in the Pacific Rim markets show that the IMF is called upon by almost all of the countries of that region for bailout packages. Thus, investigating and modeling the volatility, its characteristics, and spillover effects in emerging markets warrants further research.

In this paper we examine the effects of world market volatility on the systematic risk and volatility in four emerging Latin American markets: Argentina, Brazil, Chile, and Mexico. We choose this sample because of varying capitalization and investor composition for which reliable data are available.

Our objective is to extend previous research in two ways. First, we offer an alternative model of time-varying volatility which is an extension of the GARCH (p,q). Secondly, we examine the volatility, its persistence in four major Latin American markets, and test the volatility spillover between the world and markets under study using Granger causality tests. Thus, this paper sheds further light on the behavior of the markets under study, their relationships with the world market, and portfolio diversification effects through investing in the Latin American emerging markets.

Results suggest volatility asymmetry in Latin American emerging markets. The volatility persistence is longer in these emerging markets than in the world market. Furthermore, the volatility of Latin American emerging markets are not necessarily caused by the world market volatility and vice versa, suggesting that investors in major world markets may reduce portfolio volatility in the long-run by including Latin American equities or index funds in their portfolios.

The remainder of this paper is organized as follows. Section II describes the data, their summary statistics and time series characteristics. The proposed TARCH model, time- varying beta model, and estimation results are presented in Section III. A summary and conclusions are the subject of the last section.

II. DATA AND METHODOLOGY

Four emerging markets of varying capitalization, Argentina, Brazil, Chile, and Mexico are selected. This selection is based on the availability of time series data, which makes statistical analysis possible and reliable. The monthly data covering from December 1987 through October 1996 is derived form the Morgan Stanley International Capital Markets. Stock price indices in dollar terms are the average monthly value weighted with June 1987=100 which makes indices comparable. There are advantages in using monthly index values because they are less affected by daily or weekly noise, nonsynchronous trading problems as in daily data, and by possible trading day seasonalities and anomalies. Therefore they tend to reflect long-term volatility quite accurately (Baillie and DeGennaro [4]). The real gross domestic product in domestic currency for all countries and the exchange rates necessary to convert them to the dollar basis are taken from the OECD main Economic Indicators provided in the ISY96 CD-ROM. Using the real dollar values of G-7 (Canada, France, Germany, Italy, Japan, UK, U.S.) GNP, we compute a world value-weighted index as a proxy for the world market portfolio (see Solnik [31]).

The returns variable in each market is the percentage change in the index value times 100, i.e., $R_t = 100*[\mathrm{Ln}(\mathrm{Ind}_t) - \mathrm{Ln}(\mathrm{Ind}_{t-1})]$, where Ind is the value of the market index, and R_t represents 100 times the percentage return at a given time.

Before modeling the stock market returns, some diagnostic statistics of indices are computed. The summary statistics for the four markets and the world portfolio are presented in Table 1. The average monthly returns only in Chile and Mexico are statistically significant at the 5 percent level. The world and Chile markets are the least risky ones while Brazil, Argentina, and Mexico appear to be the riskiest markets as measured by the standard deviation of the monthly index returns. The coefficient of skewness(es) indicates that the stock returns in all and the world market are skewed and not equal to zero, as expected for a normal distribution. The kurtosis (k) for all markets except Chile also exceeds three, indicating a leptokurtic distribution. Excess kurtosis in returns of various financial series has been documented by other researchers. Bollerslev and Domowitz [8] show that excess kurtosis may be indicating serial correlation in returns variance process.

The Jarque-Bera statistic ($JB = n[s^2/6 + (k-3)^2/24]$ where n, s, and k are the observation number, skewness, and kurtosis) in all cases except Chile exceeds the critical Chi-squared statistic with two degrees of freedom, rejecting the normality of the monthly distribution of returns. Thus, the JB test verifies the initial indications of the coefficients of skewness and excess kurtosis. Finally, the standardized range, maximum minus minimum divided by the standard deviation, also is larger than six in all markets except Chile and Mexico, showing that a normal distribution generally does not fit the stock returns in the markets under consideration here except Chile. This finding confirms previous researchers' conclusion that stock returns may not be normally distributed (see Fama [13]).

Table 1

Preliminary Statistics for Monthly Return Series

Index	μ	σ	S	K	JB	SR	T
Argentina	2.58	18	0.74	5.66	41	6.3	106
Brazil	2.18	20.2	-1.42	11.20	333	8.3	106
Chile	2.52*	6.92	0.33	2.60	2.60	4.93	106
Mexico	2.17*	10.75	-0.86	5.66	44.34	3.04	106
world	0.30	3.10	-0.63	4.87	19	6.4	106

Notes: μ, σ, S, and K, are the mean, standard deviation, skewness, and kurtosis, respectively. JB is the Jarque-Bera statistic for normality test, SR, the standardized range given by (maximum-minimum)/standard deviation, and T is the observation number.
* Significant at 5 percent level.

To further analyze the stock returns' behavior in these emerging markets and the world, Ljung-Box statistic (LB, Ljung and Box [22]), Augmented Dickey-Fuller (ADF, Dickey and Fuller [11], and Phillips-Perron (PP, Phillips and Perron [27]) test statistics are computed and reported in Table 2. The LB statistic, LB(j)=T(T+2) $\Sigma_{j=1}^{L}\ r_j^2 / T-j$, where r_j is the autocorrelation coefficient of the Lth lag, T the sample size, and L the lag length, provides information regarding the autocorrelation of returns and squared returns. If there is a significant autocorrelation among stock returns in a market, then we may conclude that the market is not efficient and past values could predict future returns. It also may indicate thin trading, usually a characteristic of a small capitalization market. The significant autocorrelation coefficient among squared returns, shown by LBS(12) and excess kurtosis recorded above, may show that the returns variances follow an ARCH or GARCH process.

Table 2 also reports the findings of the ADF and PP tests of unit roots. The ADF entails estimating $\Delta\ x_t = \alpha + \beta\ x_{t-1} + \gamma_j \Sigma_{j=1}^{L}\ \Delta x_{t-j} + u_t$ and testing the null hypothesis that β=0 versus the alternative of β<1, for any x. The lag length j in the ADF test regressions is determined by the Akaike Information Criterion (AIC). The PP test estimates $\Delta\ x_t = \alpha + \beta\ x_{t-1} + u_t$ and tests the null hypothesis that β=0 versus the alternative of β<1. The PP test may be more appropriate if autocorrelation in the series under investigation is suspected. The statistics are transformed to remove the effects of autocorrelation from the asymptotic distribution of test statistic. The formula for the transformed test statistic is given in Perron [26]. The lag truncation of the Bartlett Kernel in the PP test is determined by the Newey-West's (see Newey and West [25]) rule. In both the ADF and PP tests MacKinnon's critical values (see MacKinnon [24]) are used. Accepting the null hypothesis means that the series under consideration is not stationary and unit roots are present.

Table 2.
Ljung-Box and Unit Root Test Statistics

Index	LB(12)	LBS(12)	ADF(R)	PP(R)	ADF(Ind)	PP(Ind)
Argentina	26.23*	23.23*	-4.84*	-9.83*	-2.27	-2.04
Brazil	28.04*	39.89*	-7.34*	-16.41*	-0.73	-1.36
Chile	18.25	10.73	-6.03*	-7.34*	-1.69	-2.12
Mexico	24.02*	35.08*	-5.37*	-7.85*	-2.30	-2.46
World	17.6	24.86	-5.02	-6.30*	-2.42	-2.60

Notes: LB(12), and LBS(12) are the Ljung-Box statistics of the autocorrelation of returns and squared returns. The ADF and PP stand for the Augmented Dickey-Fuller and Phillips-Perron test statistics of unit roots. The critical values of both statistics are provided by MacKinnon (1990).
* Significant at 5 percent.

Table 2 shows that LB(12), which tests the hypothesis of linear independence of returns up to twelve lags, is larger than the critical value of the Chi-Squared distribution with twelve degrees of freedom in all markets except in Chile and the world market. However, the nonlinear independence is accepted in Chile. The ADF and PP tests show that the logarithm of stock indices in all of the markets has a unit root, but that returns are stationary in all markets. In summary, the statistical evidence presented in Tables 1 and 2 suggest that the stock returns, in all markets except Chile, are not independently and identically distributed. However, using the information obtained so far, we may be able to offer models that capture stochastic properties of stock returns.

A. TARCH Model and Volatility

The excess kurtosis and statistically significant LB(12) and LBS(12) lead us to believe that there may be serial correlation in the returns variance process (see Bollerslev and Domowitz [8]). Also significant linear dependencies in the returns process imply that the conditional mean of the returns distribution may be a function of past residuals or past returns (see Scholes and Williams [29], and Lo and MacKinlay [23]).

To model the returns process, we choose the moving average model for the conditional means suggested by Scholes and Williams [29], Akigary [1], Baillie and DeGennaro [4], and Koutmos et al. [21]. In addition Bollerslev [6] and Bollerslev et al. [7] show that conditional variance of returns is also time-varying and heteroscedastic. They suggest a GARCH (p, q) for the conditional variance of returns. However, recent studies by Engle and Ng [12] and Glosten et al. [15] show that most financial series show asymmetric volatility in the sense that downward movements in markets are followed by higher volatility than upward movements of the same magnitude. For example, the expected impact of positive news is negative on the conditional variance. Glosten et al. [15] suggest a variation of the GARCH(p, q) which takes the return variance asymmetry into account. The suggested model is the Threshold GARCH or TARCH. This model includes a new term as a dummy variable, d_t, which takes the value one for bad news, when ε_t<0, and zero otherwise. Therefore, The ARCH effect is increased by the significant coefficient of the dummy variable, consistent with higher volatility associated with bad news. Thus, the returns process is modeled as MA(k)-TARCH(p,q) as follows [2]:

$$\mathrm{R}_t = \mu - \Sigma_{j=1}^{L} \theta_j \varepsilon_{t-j} + \varepsilon_t = \mu_t + \varepsilon_t, \tag{1}$$

$$\varepsilon_t \,|\, \Omega_{t-i} \sim \mathrm{N}(0, \sigma_t^2), \tag{2}$$

$$\sigma_t^2 = \phi_0 + \sum_{i=1}^{p} \phi_i \varepsilon_{t-i}^2 + \varphi\, \varepsilon_{t-1}^2\, \mathrm{d}_{t-1} + \sum_{j=1}^{q} \gamma_j \sigma_{t-j}^2, \tag{3}$$

where d_t =1 if ε_t<0 and 0 otherwise, $\phi_i \geq 0$, $\gamma_j \geq 0$, for i=0...p, and j=1,...,q. R_t represents monthly returns, μ, the unconditional mean of returns, ε_t the market innovation or residuals, μ_t and σ_t^2 are the conditional mean and variance of the returns process based on the information set Ω_{t-i} of relevant and available past data. The coefficient ϕ_i is capturing the effects of past news (innovations), φ, the asymmetrical response of volatility today to positive and negative past news and market movements, while γ captures the effects of past volatility on the current volatility. In equation (3) past positive and negative innovations are treated differently. The future effect of positive innovations (in the form of good news, for example) on the volatility is given by $\sum_{i=1}^{p} \phi_i + \sum_{j=1}^{q} \gamma_j$, while the effect of negative innovations (bad news, for example) is $\sum_{i=1}^{p} \phi_i + \sum_{j=1}^{q} \gamma_j + \varphi$, which implies higher volatility when φ statistically significant .

Estimates of equations (1) and (3) are obtained by the maximum likelihood method. The sample likelihood function for T normally distributed disturbances is given by

$$\ln L = \Sigma_{i=1}^{T} \ (-1/2)[\ln (2\pi) + \ln \sigma_t^2 + \varepsilon_t^{\ 2} / \sigma_t^2]. \qquad (4)$$

Financial data are often not normally distributed because the tails of the distribution are either too fat (platykurtic) or too slim (leptokurtic). However, in the GARCH model and its variations only conditional normality, a weaker assumption, is required. Even if the conditional normality assumption is violated, quasi-maximum likelihood estimates (maximum likelihood with invalid assumptions) are consistent but standard error estimates are inconsistent. Bollerslev and Wooldridge [9] offer robust estimates of standard errors. The Likelihood function given in (4) is maximized using Berndt, Hausman, Hall and Hall [5] (BHHH) nonlinear method with robust standard errors. Log likelihood ratio test is performed to determine the lag dimensions in equations (1) and (3), recursively. Finally, in Table 4 the portmanteau test of model adequacy, as suggested by Ljung and Box [22], and tests of normality are applied to the standardized model residuals to ensure the adequacy of estimated models.

Table 3

. Estimation of MA(k)-TARCH (p,q) Model

$$R_t = \mu + \varepsilon_t - \theta_1 \varepsilon_{t-1}$$

$$\sigma_t^2 = \phi_0 + \phi_1 \varepsilon_{t-1}^2 + \varphi \varepsilon_{t-1}^2 d_{t-1} + \gamma \sigma_{t-1}^2$$

Index	μ	θ_1	LL	R^2
Argentina	3.02	-0.022	-444.54	-0.002
	(2.22)*	(-0.17)		
Brazil	1.53	-0.07	-453.5	0.02
	(2.09)*	(-0.64)*		
Chile	2.78	0.31	-350	0.08
	(3.30)*	(3.85)*		
Mexico	1.92	0.19		
	(1.85)**	(2.10)*	-393.4	0.05
World	0.28	0.34	-1030	0.12
	(2.57)*	(3.78)*		

Index	ϕ_0	ϕ_1	φ	γ	$\phi_1+\varphi+\gamma$	HL	LR
Argentina	18	0.18	-0.29	0.89	0.78	2.79	23.74*
	(2.65)*	(1.84)**	(-1.76)**	(23.2)*			
Brazil	7.98	0.15	-0.07	0.72	0.94	11.5	25.98*
	(2.52)*	(1.92)**	(-0.72)	(33.23)*			
Chile	19.91	-0.05	-0.05	0.59	0.49	0.97	0
	(0.84)	(-0.87)	(-0.51)	(1.08)			
Mexico	15.13	0.20	-0.19	0.93	0.94	11.5	10.62*
	(2.11)*	(3.08)*	(-3.54)*	(7.28)*			
World	2.38	0.22	-0.42	0.78	0.58	1.20	9.64*
	(2.51)*	(3.36)*	(-2.99)*	(7.40)*			

Notes: t values are in parentheses. The values of the log of likelihood function, the half-life of a shock, and the likelihood ratio test are represented by LL, HL, and LR respectively. Negative R^2 is possible in heteroscedastic consistent estimation methods.
* Significant at 5 percent level.
** Significant at 10 percent level.

Maximum likelihood estimation results of equations (1) and (3) are presented in Table 3. The results for the conditional mean equation show that except for Argentina, an MA(1) model fits the returns process in all of the markets. Therefore, for these markets any month's return may be predicted by the returns of the previous month. This finding shows some degree of market inefficiency. The computed coefficient of determination, R^2, however, is quite low in all of the markets, indicating that potential for using the past information to profit financially may be quite limited. The Argentine, Brazil, and Mexican markets appear to be the most efficient by the low value of the coefficient of determination and/or the absence of linear dependency in the conditional returns process.

The maximum likelihood estimation of the coefficients of equation (3), the conditional variance of the returns process, are reported in the bottom half of Table 3. The likelihood ratio (LR= 2(ULL-RLL), where ULL and RLL are the values of the Likelihood function from TARCH (unrestricted) and homoscedastic (restricted) models, respectively, tests the hypothesis of homoscedasticity versus the time varying variance. Again the asymmetric TARCH model does not fit the volatility pattern of the Chilean market. In all other cases the LR is greater than the critical value of the Chi-squared distribution, showing statistical support for the validity of the TARCH model. Therefore, we conclude that the previous month's squared innovations or volatility has some effect on the volatility in the current month. Furthermore, the effects of the previous month's positive and negative shocks (innovations) are not symmetric.

The reported findings indicate that the past squared innovations have a significant effect on the current volatility in all markets except Brazil and Chile. The asymmetric influence of the positive and negative shocks in the previous month is statistically significant in all markets. In all markets, except Chile, the previous month's volatility has significant effect on the volatility in the current month. In summary, the TARCH (1,1) model seems to fit all markets well except Chile. Therefore, we assume that the market volatility in Chile is not heteroscedastic over time and discuss the behavior of the remaining stock markets.

The sum of estimated coefficients of the squared lagged residuals and past conditional variances from equation (3), i.e., $\sum_{i=1}^{p} \phi_i + \sum_{j=1}^{q} \gamma_j + \varphi$, measures the persistence of the past volatility. Since the conditional variance is stationary, the volatility persistence is expected to be less than one. Volatility persistence is the highest for Brazil as shown in Table 3, followed by Mexico and Argentina.

To further investigate the volatility persistence, the half-life of a shock, i.e., $HL=\ln(0.5)/\ln(\sum_{i=1}^{p} \phi_i + \sum_{j=1}^{q} \gamma_j + \varphi)$ is computed and reported in Table 3. According to this measure, volatility is more persistent in Brazil and Mexico lasting almost a year (eleven and half months) as opposed to approximately three months in Argentina.

This finding may be explained by several factors. More active small investors in a market, perhaps measured by the percentage of shares owned by individuals, could be a key to volatility persistence in a market as individual investors' sentiments might change rapidly. It may be argued that smaller investors are easily attracted to the market euphoria and sell off in slumps adding to the volatility compared with more informed and long-term institutional investors.

The varying degree of volatility persistence in the markets under study may also be influenced by the ten-firm concentration ratios, the relative share of the top ten firms' market value of equities. It may be that in a highly concentrated market, large firms are under constant watch by analysts, institutional investors, and individual investors alike, reducing chances of surprise news and sudden market jolts. On the contrary, in less concentrated markets surprise news from many firms may contribute to volatility persistence.

Returning to the model adequacy, Table 4 presents the Ljung-Box Portmanteau test of linear and nonlinear dependency of the standardized residuals (residuals divided by one step ahead conditional standard deviation) as well as JB normality test. As expected, the LB statistic for the standardized residuals and their squares has declined and in all markets is insignificant when compared with the 95 percent Chi-Squared statistic with twelve degrees of freedom. This finding indicates that the estimated models are adequately specified. However, the normality of the standardized residuals' distribution is rejected almost in all markets as indicated by the JB statistic. Nonetheless, the estimated coefficients of the model in equations (1) and (3) are still consistent under non-normality of model residuals and their standard deviation estimates are robust. The skewness, kurtosis and standardized range in almost all cases have declined in comparison to their counterparts for the original return series indicating that the fitted models are relatively successful in explaining the return generating processes in all countries.

Table 4
Diagnostic Tests on the Standardized Model Residuals

Index	LB(12)	LB^2 (12)	S	K	JB	SR	T
Argentina	4.93	7.65	0.89	4.55	24.5*	5.73	106
Brazil	13.18	3.34	-1.35	10.1	257.4*	7.75	106
Chile	10.3	6.48	0.25	2.53	2.53	4.90	106

Mexico	15.88	13.08	-0.49	3.47	5.24	5.49	106
World	12.32	17.63	-0.41	4.75	14.1*	6.12	106

Notes: LB(12), and LBS(12) are theLjung-Box statistics of the autocorrelation of returns are squared returns. μ, σ, S, K, are the mean, standard deviation, skewness, and kurtosis. JB is the Jarque-Bera statistic for normality test, SR, the standardized range given by (maximum-minimum)/standard deviation, and T is the observation number.
* Significant at 5 percent level.

B. Time -Varying Betas

To test how the world market volatility affects volatility in each of the markets under consideration, we estimate a model suggested by Schwert and Seguin [30]:

$$R_{it} = \alpha_i + \beta_{it} R_t^* + \varepsilon_{it} \quad \text{for i=1....T,} \tag{5}$$

where R_{it} is the return in a market in time t, R_t^*, the world market return, and ε_{it} the error term. The coefficient β_{it}, which measures the undiversifiable, i.e., the systematic risk in market i at time t, is given by

$$\beta_{it} = \text{cov}(R_{it}, R_t^* \mid \Omega_{t-1}) / \sigma_t^{*2}, \tag{6}$$

where σ_t^{*2} is the world portfolio's conditional variance computed from the estimated TARCH model in Table 3, and Ω_{t-1} is the set of relevant information in period t-1. The covariance in (6) may be rewritten in terms of the covariance of the returns of the markets, which constitute the world portfolio as

$$\beta_{it} = \sum_{j=1}^{N} \omega_j \sigma_{ijt} / \sigma_t^{*2}, \tag{7}$$

where ω_j is the weight (the relative GDP) of the country j in the world portfolio, and $\sigma_{ijt} = \text{cov}(R_{it}, R_{jt} \mid \Omega_{t-1})$ may be specified as a linear function of conditional variance of the world portfolio as

$$\sigma_{ijt} = \psi_{ij} + \rho_{ij} \sigma_t^{*2}. \tag{8}$$

Substituting (8) in (7) and simplifying, one arrives at

$$\beta_{it} = \sum_{j=1}^{N} \omega_j \psi_{ij} / \sigma_t^{*2} + \sum_{j=1}^{N} \omega_j \rho_{ij} . \qquad (9)$$

Setting $\sum_{j=1}^{N} \omega_j \sigma_{ij} = \eta_i , \lambda_i = \sum_{j=1}^{N} \omega_{ij} \psi_{ij}$ in (9) produces

$$\beta_{it} = \eta_i + \lambda_i / \sigma_t^{*2} . \qquad (10)$$

Equation (10) states that the time varying systematic risk in market i, comprised of a constant part stemming form characteristics of market i (η_i), is directly related to the volatility of world portfolio, σ_t^{*2} , if λ_i <0, and inversely related to it if λ_i >0. It is expected that λ_i <0 (>0) in markets with a high (low) degree of correlation with the world portfolio. In order to estimate the parameters of equation (10), we substitute (10) in (5) to obtain equation (11):

$$R_{it} = \alpha_i + \eta_i R_t^* + \lambda_i R_t^* / \sigma_t^{*2} + \varepsilon_{it} , \qquad (11)$$

which is the basis for estimating the time-varying effect of the world portfolio volatility on the systematic risk and returns in a market.

The heteroscedasticity consistent coefficient estimates of equation (11) are obtained by the Newey-West [25] methodology and reported in Table 5. Equity returns in all of these emerging markets are positively correlated with the world equity market return as shown by a positive η_i , but all are statistically insignificant. The systematic risk in Chile and Mexico are directly, and in Argentina and Brazil are inversely related to the volatility of the world portfolio, but all coefficients are statistically insignificant. The values of the coefficient of determination show that these emerging markets are not strongly related with the world market. This finding is not surprising as it is well known that market movements in most emerging markets are not affected by the factors that move the markets of the industrialized economies. Furthermore, the simple correlation coefficients between equity markets of Argentina, Brazil, Chile, and Mexico with the world equity market are 0.16, 0.16, 0.12, and 0.30, respectively. In contrast, the correlation coefficients between the U.S. and UK equity returns and the world portfolio are 0.69 and 0.66, respectively.

Table 5.
Heteroscedastic consistent OLS Estimates for Time-Varying Betas

$$R_{it} = \alpha_i + \eta_i R_t^* + \lambda_i R_t^* / \sigma_t^{*2} + \varepsilon_{it},$$

$$\sigma_t^{*2} = \phi_0 + \phi_1 \ \varepsilon_{t-1}^2 + \varphi \ \varepsilon_{t-1}^2 \ \mathrm{d}_{t-1} + \gamma_1 \ \sigma_{t-1}^*$$

Index	α_i	η_i	λ_i	R^2
Argentina	2.35	0.36	5.66	0.02
	(1.18)	(0.29)	(0.56)	
Brazil	1.84	1.01	1.11	0.026
	(0.95)	(0.76)	(0.08)	
Chile	3.15	0.42	-1.24	0.016
	(4.11)*	(0.63)	(-0.22)	
Mexico	2.16	1.48	-3.37	0.09
	(1.85)**	(1.46)	(-0.41)	

Notes: t values are in parentheses.
* Significant at 5 percent level.
** Significant at 10 percent level.

To further examine the relationship between the world market and the markets under study, we estimate bivariate vector autoregressive models (VAR) of world market volatility and the volatility in markets in question. The VAR model to be estimated is as follows:

$$\begin{bmatrix} 1-\alpha_{11}(L) & -\alpha_{12}(L) \\ -\alpha_{21}(L) & 1-\alpha_{22}(L) \end{bmatrix} \begin{bmatrix} \sigma_t^{*2} \\ \sigma_{mt}^2 \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}, \qquad (12)$$

where $\alpha_{11}(L) \ldots \alpha_{22}(L)$ are nth order scalar polynomials in the lag operator L, σ_t^{*2} and σ_{mt}^2 represent volatility in the world market and a market under study, respectively, β_i, model constants, and $u_t = [u_{1t} u_{2t}]$ is a vector of white noise residuals process.

In the VAR system (12) the order of polynomials $\alpha_{11}(L)...\alpha_{22}(L)$, which determines model dimensionality, is set by minimizing the Akaike Information Criteria (AIC) given by AIC(p) = ln det $(\sum_u)$+2(M^2 *p)/T, where $\sum_u$ is the residuals covariance matrix of VAR(p) systems, T and p are the number of observations and the lag order and in the VAR.

The estimated system of VAR in (12) may be used to examine Granger causality between the world and individual market volatility. The null hypothesis that the volatility in a market does not Granger cause the world market volatility is accepted if all the parameters of the polynomial $\alpha_{12}(L)$ are equal to zero. Conversely, volatility in each of the markets is not Granger caused by the world market volatility if the parameters of the polynomial $\alpha_{21}(L)$ are all statistically insignificant. The appropriate F ratio is F=((SSEr-SSEu)/r)/(SSEu/T-k), where SSEr and SSEu are the sum of squared errors from restricted and unrestricted versions of each equation in the VAR system in (12), T, k, and r are the observation number, the number of parameters of the unrestricted (full) model, and the number of restrictions (parameters which are equal to zero on the right-hand-side). A significant F rejects the null hypothesis, indicating that causality between two variables cannot be rejected.

The causality test results from the VAR system in (12) are presented in Table 6. The insignificant F values in all cases suggest that the world market have no causal effect on the volatility of the emerging markets under study. This finding further shows that the of Latin American and world equity markets are not yet integrated. There is also no evidence of feedback, i.e., the volatility in Latin American markets does not Granger cause the world market volatility, with the exception of Brazil. The findings of Granger causality test may also support findings of Harvey [18] that emerging equity markets are weakly correlated with the more developed world markets

Table 6.
Estimation Results of Granger causality tests

$$\begin{bmatrix} 1-\alpha_{11}(L) & -\alpha_{12}(L) \\ -\alpha_{21}(L) & 1-\alpha_{22}(L) \end{bmatrix} \begin{bmatrix} \sigma_t^{*2} \\ \sigma_{mt}^2 \end{bmatrix} + \begin{bmatrix} \beta_1 \\ \beta_2 \end{bmatrix} = \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}$$

	σ_t^{*2} does not cause σ_{mt}^2 $H_0: \alpha_{21}(L)=0$	σ_{mt}^2 does not cause σ_t^{*2} $H_0: \alpha_{12}(L)=0$
Argentina	0.52	0.31
Brazil	1.38	10.13*

Mexico	0.76	1.09

Notes: σ_t^{*2} and σ_{mt}^2 are the volatility in the world market and a market under study. The numbers in the table are the F value given by F=((SSEr-SSEu)/r)/(SSEu/T-k), where SSEr and SSEu are the sum of squared errors from restricted and unrestricted versions of each equation in the VAR system in (13), T, k, and r are the observation number, the number of parameters of the unrestricted (full) model, and the number of restrictions (parameters which are equal to zero on the right-hand-side). The dimension of lags on the right- hand -side of VAR models is determined by minimizing AIC. Insignificant F values indicate no causal relationship.

IV. SUMMARY AND CONCLUSIONS

In this paper we examine the volatility in four emerging Latin American markets, Argentina, Brazil, Chile, and Mexico. Monthly value weighted index returns are computed and analyzed. A moving average TARCH model, which accounts for asymmetry, is estimated.

Our findings show that the past squared innovations have significant effects on the current volatility in most markets and the world. The asymmetric influence of the positive and negative shocks in the previous month is statistically significant in Argentina and Mexico. In all markets except Chile, the previous month's volatility has significant effects on the volatility in the current month. In summary, the TARCH (1,1) model seems to fit all markets but Chile well.

All markets show high volatility persistence relative to the world market. However, returns and systematic risk in the Latin American emerging markets are found to be independent of the world market. Granger tests of causality verify that the volatility in Latin American emerging markets is independent of the world market volatility and vise versa. In conclusion, equities in this sample show a higher than world market volatility persistence. Furthermore, the volatility in these equity markets is not necessarily caused by the world market volatility. Therefore, investors may reduce risk by including Latin equities or index funds in their portfolios.

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NOTES

1. The Wall Street Journal on November 25, 1997, page C1 in an article entitled "Mutual Funds Brace for More Asian Pain," reports that T. Row price New Asia dropped 36.4% and Dean Witter Pacific Growth was down 35.6%, since December 1996. The article predicts that matters could get worse without an IMF loan. A similar article, "Aversion to Emerging Markets Grows," November 17, page C1, states that the volatility of the Pacific Basin markets has moved to Latin American mutual funds as well as other international funds.
2. Note that the TARCH models, much the same as EGARCH models are more flexible than ARCH or GARCH models and can accommodate conditional skewness shown in financial data. For more on the subject see Hsieh [19].

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