Stability, Volatility, Risk Premiums, and Predictability in Latin American Emerging Stock Markets

Mahfuzul Haque*
Indiana State University

M. Kabir Hassan
University of New Orleans

Oscar Varela
University of New Orleans

This study investigates the stability, volatility, risk premiums, and persistence of volatility in the standardized 1988-98 exchange-converted U.S. dollar equity returns of Argentina, Brazil, Chile, Columbia, Mexico, Peru, and Venezuela. All markets, except Argentina, Colombia, and Mexico, have time-varying risk premiums, indicative of risk aversion, and all markets have ARCH/GARCH effects, except Venezuela, which also offer the best potential diversification gains because of low correlation. This study also investigates returns' predictability both in U.S. dollars and local currency. The predictability results are mixed, with better results when using local currency. The nonparametric runs test rejects weak form efficiency for all markets. Venezuela and Chile are not stable. Residual kurtosis or fat tails are present in all markets; Argentina, Colombia, and Peru have serial correlation; shocks to volatility are persistent only in Brazil. In general, Latin American emerging markets have shown remarkable performance using return to risk measures; predictability seems mixed; and the Latin American emerging markets have volatility clustering with shocks that decay with time.

Introduction

Emerging markets' equity flows have increased recently, with market capitalization growing at nearly double the rate of the world's equity market. Latin America's

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emerging equity markets have concurrently experienced numerous changes, some in economic policy. For example, Mexico suffered economic crises with the peso collapse in 1994, just two years after NAFTA. In 1991 Argentina changed its currency policy, assigning one Argentine peso a value equal to one U.S. dollar, with Brazil following in 1994. Privatization of state-owned enterprises have occurred, economic stabilization programs have been enacted, and these markets have opened to foreign investments at unprecedented levels, with foreign portfolio capital pouring into the region and its market size growing rapidly. The environment in Latin America now involves policies that are more market leaning with corporate sector restructuring. These events over the past decade demand continued research into the performance of the Latin American stock markets, for their ability to transfer saving into investment has major implications for the region's growth and development.

This paper examines, within the context of this environment, the stability, volatility, risk premiums, and persistence of volatility in the 1988-98 exchange-converted U.S. dollar equity returns of Argentina, Brazil, Chile, Columbia, Mexico, Peru, Venezuela, and the Latin America (LA) index. It also examines these markets' predictability, using U.S. dollars and local currency returns, to test the robustness of predictions. This study uses a battery of statistical methods and a relatively large sample of Latin American countries, unlike previous studies usually limited to a smaller set or a single country. It aims to examine these emerging markets robustly, as understanding the performance of these markets is important to portfolio managers and policy makers alike.

In general, coefficient stability for Box-Jenkins ARMA representations of weekly returns, volatility effects of expected returns in GARCH frameworks, and the predictability of equity returns are examined. The findings suggest that Latin American emerging markets have shown remarkable performance using return to risk measures, have volatility clustering with shocks that decay with time, and are mixed in terms of predictability.

Literature

Returns, volatility and correlations, and the clustering, persistence, and forecastability of volatility are the subject of this review, in accord with the application of these to Latin America's emerging markets.[1]

[1] A large body of evidence exists against random walks for stock returns (Summers, 1986; Fama and French, 1988; Lo and MacKinlay, 1988; and Poterba and Summers, 1988). Most studies are conducted on the world's largest stock markets including the U.S., Japan, and Europe, with relatively little research on the equity markets of the developing markets. Errunza and Losq (1985) and Lessard (1973) are exceptions. Also, Urrutia (1995) uses the variance ratio methodology to test four Latin American equity markets and rejects the random walk hypothesis. A runs test shows that these are weak form efficient.

Expected returns in emerging markets can be impressive at times, but are highly volatile. Barry and Rodriguez (1997) find that the risk and return performance in Latin America's equity market has been among the most volatile in the world. Generally, the literature documents low correlations between emerging and developed market returns, creating a basis for diversification benefits owing to risk reductions associated with international portfolios involving emerging and developed markets.[2] Gooptu (1993) finds increasing equity flows to developing countries.

Risk and return relationships can be unclear across time periods, leading to more volatility. Normally, returns and risk premiums are directly related to the asset's variance and covariance with the market portfolio (Sharpe, 1964; Lintner, 1965; Mossin, 1966; and Black and Scholes, 1974). Glosten, Jagannathan, and Runkle (1993), however, claim that across time periods there is no agreement about the relation between risk and return. Investors may not demand a high-risk premium if the risky time periods coincide with periods when investors, better able to bear risk, are less risk averse. A riskier expected future may motivate investors to save more now, lowering the premia.[3]

Volatility clustering has a long history as a salient empirical regularity characterizing highly speculative prices, but not until recently has the importance of explicitly modeling time-varying second order moments been recognized. Engle's (1982) ARCH, Bollerslev's (1986) GARCH (q,p), and Engle's (1987) GARCH (q,p)-M models provide methods for modeling the conditional mean as an explicit function of conditional variance. Bollerslev, Chou, and Koner (1992) overview some of the developments in the formation of ARCH models and survey their numerous empirical applications in finance.[4]

Persistence of volatility (spillovers) is necessary, according to Poterba and Summers (1986), if volatility is to have a significant impact on equity values. Wei, Liu,

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[2] Even among developed markets, studies by Agmon (1972), Granger and Morgenstern (1970), Grubel and Fadner (1974), Lessard (1976), and Levy and Sarnel (1970) found little or no covariation in the 1960s and 1970s. The general impression of these studies is that stock markets across borders are segmented. Later period studies by Panton, Lessig, and Joy (1976), Hilliard (1979), Watson (1980), Philippatos, Christofi, and Christofi (1983), and Meric and Meric (1989) corroborate the earlier findings.

[3] Regardless, U.S. investments abroad do not appear to be the source of excess volatility or higher turnover in local equity markets. Tesar and Werner (1995) conclude that despite recent increases in investments in foreign equities, U.S. portfolios remain biased toward domestic equities. There is no evidence of a relation between the volume of U.S. transaction in foreign equities and local turnover rates or volatility of stock returns.

[4] Regarding GARCH-M, Chou (1988) states that this model provides a more flexible framework to capture various dynamic structures of conditional variance and allows simultaneous estimation of parameters of interest. Bollerslev (1992) states that GARCH-M provides a natural tool for investigating the linear relationship between the return and variance of the market portfolio provided by Merton's (1973,1980) intertemporal CAPM. Engle (1990) advocates the use of the GARCH (q, p)-M in testing for stock market volatility.

Yang, and Chaung (1995) find no volatility spillover effects in New York, London, Tokyo, Hong Kong, and Taiwan using a GARCH (1,1) model. But Gallant, Rossi, and Tauchen (1992) find positive correlation between conditional volatility and volume, with large price movements followed by high volume, conditioned on lagged volume, and positive risk-return relationships.

Akgiray (1989) presents various forecasts of market volatility and compares their accuracy. The predictive capabilities of the ARCH and GARCH models provide evidence of their usefulness as practical models of stock returns. Choudhry (1996) finds an ARCH effect using a GARCH (q, p)-M model for all six emerging markets and the persistence of volatility before and after the 1987 crash.

French, Schwert, and Stambaugh (1987) and Campbell and Hentschel (1992), using a QGARCH model of changing variance as proposed by Engle (1990) and Sentana (1991), find evidence of a positive association. But Glosten, Jagannathan, and Runkle (1993) using GARCH-M and Nelson (1991) using EGARCH observe a negative intertemporal relation for the U.S. stock market. Bekaert and Wu (2000) find that volatility in equity markets is asymmetric with returns and conditional volatility negatively correlated. Wu (2001), following Campbell and Hentschel (1992), develops an asymmetric volatility model and also finds that volatility in equity markets is asymmetric.

Koutmos and Booth (1995) investigate the transmission mechanism of price and volatility spillovers across the New York, Tokyo, and London stock markets and find strong evidence that volatility spillovers in a given market are pronounced. Koutmos and Booth (1998) find a significant inverse relationship between volatility and autocorrelation in six major industrialized countries' stock markets. Campbell, Grossman, and Wang (1993) find that trading volume and stock returns' autocorrelation are inversely related for U.S. stock indexes. Sentana and Wadhwani (1992) document sign reversals in U.S. return autocorrelations, such that low (high) volatility is associated with positive (negative) autocorrelation. Koutmos (1994) reports similar findings for European exchange rates.

It appears that many inter-market return relationships worldwide have stable and low cross-correlation matrices permitting effective portfolio diversification. But Latin America has proven to be volatile over the last 20 years. There also seems to be some persistence of volatility and lower levels of predictability in emerging markets. Risk premiums, however, are expected to vary depending on the investor's willingness to take risk. Finally, U.S. investments in foreign equities, despite recent increases, do not appear to be a source of their excess volatility.

Harvey (1991a), Bekaert and Hodrick (1992), Harvey and Hamao (1992), Harvey and Ferson (1993, 1994), and Harvey, Solnik, and Zhou (1994) have all documented the existence of predictable variation in developed country returns. Recent evidence of predictable variation in the emerging market returns has been documented in Bekaert (1995), Harvey (1993a,b, 1995), and Claessens, Dasgupta, and Glen (1995). Harvey (1993) reports that stock returns of the emerging countries are highly predictable and have low correlations with developed markets. Poterba and Summers (1988) indicate that stock index returns may show positive autocorrelation if some of the securities in the index trade infrequently. The conclusion from the studies is that predictability of returns is more likely to be influenced by local information.

Data

This study uses the International Finance Corporation's (IFC) weekly stock market index data from December 30, 1988 through June 5, 1998 for Argentina, Brazil, Chile, Columbia, Mexico, and Venezuela, as well as the IFC Latin America index (which includes these seven countries). In the case of Peru, the observations start on January 1, 1993. In all cases the start date coincides with the inception of the country's status as an *emerging market*. The weekly observations contrast to most other studies, which use either yearly or monthly data. Table 1 shows the U.S. dollar (U.S. $) market capitalization and number of stocks in each index as of June 5, 1998, the ending period of this study. For comparison purposes, we also show these statistics for the IFC Composite Global index. Latin America accounts for 16.8 percent of the stocks in the composite global index (332 Latin stocks divided by 1,980 total stocks) and 29.7 percent of the composite global market capitalization.

Table 1—Latin America's Emerging Markets' Weights in the International Finance Corporation's Indices, June 5, 1998

Country Index	Number of Stocks	Market Capitalization (U.S. $ millions)	Weights in IFC Latin America Index (%)	Weights in IFC Composite Global Index (%)
Argentina	35	31.316.74	11.5217	3.4239
Brazil	87	91.070.88	33.5058	9.9568
Chile	53	37.954.34	13.9637	4.1495
Colombia	27	8.156.57	3.0009	0.8918
Peru	37	9.441.57	3.4736	1.0322
Mexico	74	88.029.97	32.387	9.6243
Venezuela	19	5.836.25	2.1472	0.6381
		271.806.32	100	29.7166
IFC Composite Global Index				
Latin America	332	271806.33		29.7166
Asia	1078	345049.96		37.7243
EMEA	570	297806.07		32.5591
Composite	1980	914662.36		100

Note: EMEA refers to the Europe, Middle East, and Africa index

These indexes, based on value-weighted portfolios, are designed to serve as benchmarks that are consistent across national boundaries and include stocks that satisfy criteria related to size, liquidity, and industry. They include the largest and most actively traded stocks in each market, targeting sixty percent of both total market capitalization at the end of each year and trading volume during the year. Size is measured by market capitalization, and liquidity is measured by the value of shares traded during the year. Only stocks listed on one of the major exchanges in the emerging markets are included in an index. Stocks are excluded when the issuing company is headquartered in an emerging market but listed only on foreign markets. Even though many stocks meet the liquidity and size criteria, only one or two are needed, and among these are stocks representative of industries in the emerging market. These indexes, calculated by IFC since 1981, do not take into consideration restrictions on foreign ownership and are calculated in local currencies as well as in U.S. dollars.

When necessary, the conversion to the U.S. dollars for most markets uses exchange rates taken from the *Wall Street Journal* and *Financial Times*. In the case of a multiple exchange rate system, IFC uses the nearest equivalent free market rate or the rate that would apply to repatriation of capital and income. Also, to ensure consistency, IFC only adds or deletes stocks when coverage drops below 50 percent or rises above 70 percent of the total market capitalization.

Most often, nominal excess returns (inclusive of dividends) based on U.S. dollars are used for all markets rather than local currency returns, as these provide a uniform medium to compare the performance of one market to another. The comparison is standardized because inflation differences between countries are captured somewhat with the exchange-converted U.S. dollars returns, given that these incorporate inflation through purchasing power parity and the international Fisher effect. To examine the robustness of the predictability results, however, the analysis for these tests also is performed using local currency returns.

The summary statistics for the exchange-converted U.S. dollar weekly returns of the seven Latin America emerging stock markets studied and the LA index are shown in Table 2. All markets have positive mean returns. Chile has the highest Sharpe ratio, followed by Colombia, Mexico, Peru, Argentina, Brazil, and Venezuela. All markets have excess kurtosis, signifying fatter tails, and the Jarque-Bera test decisively rejects normality in all markets.

The correlation matrix among these returns is provided in Table 3 and shows that the correlation among markets seems to be high, except Venezuela. The highest correlation that Venezuela has is with Argentina (0.5303) and the lowest is with Peru (0.1566), with most at 0.30 or less. Overall these allow some opportunity for diversification benefits.

Table 2—Summary Statistics Latin American Index and Latin American Emerging Markets Weekly Returns, 1988-98 (U.S. $)

INDEX	Mean	St Dev	SR	SK	EKU	Max	Min	J-B Stat	SL
Latin America (493 Observations)	0.427	3.473	0.123	-0.693	2.589	11.283	-15.739	22.988	0.000
Argentina (493 Observations)	0.898*	8.787	0.102	0.820	9.575	53.587	-51.245	1892.260	0.000
Brazil (493 Observations)	0.631**	7.439	0.085	-0.231*	1.916	23.257	-37.200	77.213	0.000
Chile (493 Observations)	0.458	3.013	0.152	0.260*	1.294	11.517	-13.208	38.501	0.000
Colombia (493 Observations)	0.484	3.692	0.131	1.560	8.481	26.981	-13.165	1682.410	0.000
Mexico (493 Observations)	0.422*	3.859	0.109	-0.864	5.379	14.443	-26.075	639.265	0.000
Peru (284 Observations)	0.428**	3.952	0.108	0.771	2.683	18.327	-9.210	108.494	0.000
Venezuela (493 Observations)	0.450**	5.908	0.076	-0.73	12.516	26.249	-50.692	3189.900	0.000

Source: International Finance Corporation's (IFCs) weekly stock market index data from December 30, 1988 through June 5, 1998 for Argentina, Brazil, Chile, Columbia, Mexico, and Venezuela, as well as the IFCs Composite Global and Latin American indexes. In the case of Peru, the observations start on January 1, 1993. In all cases the start date coincides with the inception of the country's status as an emerging markets. SR refers to the Sharpe ratio, SK to skewness, EKU to excess kurtosis, and SL to significance level. The Jarque-Bera normality test statistic (J-B Stat) is a joint test for skewness and kurtosis of the disturbances and is asymptotically distributed as chi-squared random variable with two degrees of freedom under a null of normality

* Significant at the 1 percent level (difference of mean, SK, or EKU)

** Significant at the 5 percent level (difference of mean, SK, or EKU)

*** Significant at the 10 percent level (difference of mean, SK, or EKU)

Table 3—Correlation Coefficients Among Latin American Emerging Markets Weekly Returns, 1988-98 (U.S. $)

Index	Argentina	Brazil	Chile	Colombia	Mexico	Peru	Venezuela
Argentina	1.00000	0.86380	0.86740	0.86570	0.78030	0.82570	0.53030
Brazil		1.00000	0.85380	0.81850	0.51810	0.93780	0.26690
Chile			1.00000	0.91650	0.60950	0.91430	0.30050
Colombia				1.00000	0.73710	0.85660	0.29230
Mexico					1.00000	0.49630	0.51190
Peru						1.00000	0.15660
Venezuela							1.00000

Source: International Finance Corporation's weekly stock market index data from December 30, 1988 through June 5, 1998 for Argentina, Brazil, Chile, Columbia, Mexico, and Venezuela and from January 1, 1993 through June 5, 1998 for Peru. The start date coincides with the inception of the country's status as an emerging market. Correlations for Peru are restricted to the time period for which the Peru data are available

Methodology

Stability. The following Box-Jenkins (1976) ARMA (p, q) model is used to test for stability for each emerging market and the Latin America index,

$$y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots\ldots \alpha_p y_{t-p} + \varepsilon_t + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + \ldots\ldots\ldots \beta_q\varepsilon_{t-q} \qquad (1)$$

where:

y_t = The returns for each market/index (t = 1 to T);
α_i = The coefficient on the lagged returns (i = 1 to p);
ε_t = The autoregressive error term; and
β_j = The coefficient on the lagged error terms (j = 1 to q).

Once the appropriate model in equation (1) is identified and estimated, then it is checked for structural stability. The sample of T observations is split, with m in the first and n (equal to T - m) in the second.[5] Then the model is identified and estimated for each sub-sample, with the coefficients for the first given by α_{i1} and β_{j1} and the second by α_{i2} and β_{j2}. The F-test is used to test the null hypotheses of no structural change or that the corresponding coefficients for each sub-sample are equal (α_{i1} equals α_{i2} and β_{j1} equals β_{j2}). If the F-test cannot reject the null and α_i is positive, then the returns for the market/index are deemed stable over time.

Volatility, Risk Premiums, and Persistence of Volatility. The GARCH (q, p)-M methodology (Engle, 1982; Bollerslev, 1986; Engle and Bollerslev, 1986; and Engle *et al*., 1987) is used to examine the volatility, risk premiums, and persistence of volatility. In this approach, the conditional variance at time t, h_t (equal to $E_{t-1}\varepsilon_t^2$), is equal to

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2} + \sum_{i=1}^{p} \beta_i h_{t-i} \qquad (2)$$

where the ARCH model for ε_t is

$$\varepsilon_t = v_t(\alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^{\ 2})^{1/2}.$$

The return-generating process is specified by

$$y_t = \mu_t + \delta * h_t^{1/2} + \varepsilon_t \qquad (3)$$

where $\varepsilon_t \sim N(0, h_t)$.

The size of α_i in equation (2) indicates the magnitude of the effect imposed by the lagged error term ε_{t-i} on the conditional variance h_t and, if significant, implies the existence of an ARCH process in the error terms (volatility clustering). If the size of the sum of α_i and β_i in equation (2) equals one, then current shocks persists indefinitely in conditioning the future variance. It also represents the change in the response function of shocks to volatility per period, such that a value more (less)

[5] Samples for the seven Latin American markets are split in equal parts for the F-test.

than unity implies that the response function of volatility increases (decreases) with time.

The presence of $h_t^{1/2}$ in equation (3) provides a way to directly study the explicit trade between risk and expected return. The significant influence of volatility on stock returns is captured by the coefficient δ of $h_t^{1/2}$, as it represents the index of relative risk aversion (time-varying risk premium). A significant and positive δ implies that investors are compensated with higher returns for bearing higher risk, while a significant and negative coefficient δ implies that investors are penalized for bearing risk.

Predictability. The Ljung-Box Q statistic is used to test for the Box-Jenkins model's adequacy and predictability of returns. The individual t-statistics are obtained from the autocorrelation functions (ACF). The Lo and MacKinlay (1988) variance ratio test (using q week holding periods) is used to test for a random walk in returns (that they are identical and independently distributed and a linear function of the holding period). Deviations from a random walk can indicate some form of return predictability.

Mean and variances are calculated as follows,

$$\hat{\mu} = \frac{1}{nq}\sum_{k=1}^{nq}(X_k - X_{k-1}) = \frac{1}{nq}(X_{nq} - X_0)$$

where μ = mean and q = 1

$$\overline{\sigma}_a^{\,2} = \frac{1}{nq-1}\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2$$

where σ_a^2 = variance and nq + 1 = total observations.

$$\overline{\sigma}_c^{\,2} = \frac{1}{m}\sum_{k=q}^{nq}(X_k - X_{k-q} - q\hat{\mu})^2$$

where σ_c^2 = variance of observation with q > 1 and m = q (nq – q + 1)(1 – q/nq).

Variance ratios are calculated as,

$$\overline{M}_d(q) = \overline{\sigma}_c^{\,2} - \overline{\sigma}_a^{\,2}$$

$$\overline{M}_r(q) = \frac{\overline{\sigma}_c^{\,2}}{\overline{\sigma}_a^{\,2}} - 1 .$$

Under a heteroscedastic increment, the statistics $\overline{M}_d(q)$ and $\overline{M}_r(q)$ all converge almost to zero for all q as n increases without bound.

Both $\delta(j)$ and $\theta(q)$ are heteroscedasticity-consistent estimators,

$$\hat{\delta}(j) = \frac{\sum_{k=j+1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2 (X_{k-j} - X_{k-j-1} - \hat{\mu})^2}{\left(\sum_{k=1}^{nq}(X_k - X_{k-1} - \hat{\mu})^2\right)^2}$$

$$\hat{\theta}(q) \equiv \sum_{j=1}^{q-1}\left[\frac{2(q-j)}{q}\right]^2 \hat{\delta}(j)$$

and

$$Z^*(q) = \frac{\sqrt{nq}\,\overline{M}_r(q)}{\sqrt{\hat{\theta}}}.$$

Under the null hypothesis, the value of the variance ratio is one and the test statistic has a standard normal distribution (asymptotically). When the variance ratio is greater than one, then returns are considered predictable.

Weak form market efficiency is examined using a runs test (Levene, 1952) used by Urrutia (1995). This is a nonparametric test used for detecting the frequency of the changes in the direction of a time series. The runs test determines whether the total number of runs in the sample is consistent with the hypothesis that changes are independent. The standard normal Z-test statistic used to conduct a runs test is given by:

$$Z = (M - E(M)) / [\delta^2(M)]^{1/2}$$

where:

M	=	The actual number of runs;
E(m) [equal to (2N-1)/3]	=	The expected number of runs;
$\delta^2(M)$ [equal to (16N-29)/90]	=	The variance of M runs; and
N	=	The number of observations.

Positive (negative) Z-values indicate the sample contains greater (less) than the expected number of runs.

Empirical Results

The stability F-statistic test results in Table 4 show that, at the one percent level, returns are not stable for Chile and Venezuela. Recall that the ARMA model is estimated for two sub-samples. The F-statistic tests whether the coefficients for each sub-sample are equal, indicative of no structural change. In Table 4, these F-statistics are significant at one percent for Chile and Venezuela. These markets during the period of this study may have gone through a process of institutional changes, in line with research that suggests that institutional features and changes in emerging markets can be a factor underlying instability (Roll, 1989).

The volatility, risk premiums, and persistence of shocks to volatility for all markets, including the Latin America index, are reported in Table 5, along with the results for skewness, excess kurtosis, and Q statistics for the residuals. All markets, except Venezuela, have ARCH/GARCH effects (via the significance of the α and β coefficients), evidence of significant volatility clustering. But shocks are not explosive throughout because the ARCH parameter α (in model 3, Table 5) is significantly less than unity. The significant influence of volatility on stock returns is captured by the term $\delta^* h_t^{1/2}$ (in model 1, Table 5). The coefficient δ represents an index of relative risk aversion (or time-varying risk premium). This coefficient is significantly positive for Argentina, Colombia, Mexico, and the Latin America index

Table 4—Stability Test Summary Statistics for Latin America Index and Latin American Emerging Markets, Weekly Returns, 1988-98 (U.S. $)

						Stability Test	
Index	Model	Coeff	Estimate	t-stat	SL	F-stat	SL
Latin America	AR (2)	AR (1)	0.11421**	2.53949	0.01141	0.82023	0.4409
493 Observations		AR (2)	0.1172*	2.60543	0.00946		
Argentina	ARMA (2 , 2)	AR (1)	-0.46864*	-5.43379	0.00000	0.28165	0.8899
493 Observations		AR (2)	- 0.82367*	-11.054	0.00000		
		MA (1)	0.38158*	4.38407	0.00001		
		MA (2)	0.82186*	10.67185	0.00000		
Brazil	AR (1)	AR (1)	0.10542**	2.34637	0.01935	3.26394***	0.0714
493 Observations							
Chile	AR (3)	AR (1)	0.14447*	3.20457	0.00144	5.19738*	0.0015
493 Observations		AR (2)	0.09851**	2.16916	0.03055		
		AR (3)	0.10347**	2.30666	0.02149		
Colombia	AR (1)	AR (1)	0.15632*	3.49382	0.00052	0.09521	0.7578
493 Observations							
Mexico	AR (2)	AR (1)	0.16662*	3.73936	0.00021	0.15739	0.8544
493 Observations		AR (2)	0.17903*	4.01386	0.00007		
Peru	ARMA (1 , 1)	AR (1)	0.50777**	2.13296	0.0338	0.86773	0.421
284 Observations		MA (1)	-0.43121***	-1.70115	0.09002		
Venezuela	ARMA (1, 1)	AR (1)	0.78823*	4.68666	0.00000	5.32534*	0.0052
493 Observations		MA(1)	-0.72628*	-3.85881	0.00013		

Note: Results are based on a Box-Jenkins ARMA (p,q) model, with the structural stability tested using two evenly split sub-samples of the appropriate model with the F-test used to test for the null hypothesis of no structural change or that the corresponding coefficients for each sub-sample are equal. SL denotes the significance level of the F-test. The individual t-test statistics are obtained under the null hypothesis that the coefficient is equal to zero.

* Significant at the 1 percent level

** Significant at the 5 percent level

*** Significant at the 10 percent level

Table 5—GARCH (1, 1)-M Results for Latin America Index, and Latin American Emerging Markets Model Weekly Returns, 1988-98 (U.S.$)

1) $y_t = \mu_t + \delta_t * h_t^{1/2} + \varepsilon_t$ — y_t = stock index return.

2) $\varepsilon_t / \psi_{t-1} \sim N\ (0, h_t)$ — μ_t = mean y_t, conditional on past information (ψ_{t-1})

3) $h_t = \alpha 0 + \Sigma^q_{i=1} \alpha_i * (\varepsilon_{t-i})^2 + \Sigma^p_{i=1} \beta_i * h_{t-i}$ — $\alpha 0 > 0, \alpha_i \geq 0, \beta_i \geq 0$

Returns (U.S. $)	μ	δ	$\alpha 0$	α	β	$(\alpha+\beta)$*	LF	Ku	Sk	Q (30)
Latin America	0.00366	0.12792666643*	0.00012	0.23019	0.69142	0.92161	1425.58	3.19152	-0.7812	33.16
493 Observations	{2.31335}	{2.73536}	{2.98052}	{3.66197}	{10.15726}	({3.470385})				
	[0.02112]	[0.00623]	[0.00288]	[0.00250]	[0.00000]	[0.06248]		[0.00000]	[0.00000]	[0.10086]
Argentina	0.00515	0.234810601***	0.001599	0.453313	0.154313	0.60763	1053.43	11.0044	-0.2197	181.35
493 Observations	{1.29940}	{1.79169}	{2.32825}	{7.46619}	{6.76615}	({41.79476})				
	[0.19423]	[0.07318]	[0.01990]	[0.00000]	[0.00000]	[0.00000]		[0.00000]	[0.04708]	[0.00000]
Brazil	0.00349	0.07112	0.00006	0.16487	0.84525	1.01011	1067.41	3.64184	-0.6364	34.4058
493 Observations	{1.02364}	{1.61666}	{1.66180}	{4.06460}	{25.08010}	({0.369607})				
	[0.30651]	[0.10595]	[0.09655]	[0.00005]	[0.00000]	[0.54324]		[0.00000]	[0.00000]	[0.09952]
Chile	0.004130	0.07081	0.00019	0.19929	0.58735	0.78664	1494.16	1.8229	0.03513	23.99
493 Observations	{3.05694}	{1.57287}	{1.98606}	{3.49203}	{4.11343}	({3.412986})				
	[0.00236]	[0.11575]	[0.04703]	[0.00048]	[0.00004]	[0.06469]		[0.00000]	[0.75089]	[0.404316]
Colombia	0.00417	0.0751306***	0.00027	0.33199	0.46320	0.7973	1437.40	5.96737	1.05157	62.039
493 Observations	{2.57884}	{1.74194}	{1.92267}	{2.36727}	{2.11652}	({3.65987})				
	[0.01020]	[0.08152]	[0.05452]	[0.01792]	[0.03430]	[0.05574]		[0.00000]	[0.00000]	[0.00005]
Mexico	0.003456	0.1557930456*	0.000167	0.239424	0.672954	0.91238	1377.63	7.82624	-1.1013	32.5471.
493 Observations	{1.95020}	{3.62348}	{2.19989}	{3.25479}	{6.90585}	({2.404720})				
	[0.051721]	[0.000291]	[0.027815]	[0.00114]	[0.00000]	[0.12096979]		[0.00000]	[0.00000]	[0.1140]
Peru	0.00352	0.04929	0.00030	0.10563	0.57244	0.67807	772.435	2.63671	0.62096	44.314
284 Observations	{1.52073}	{0.64781}	{2.15712}	{2.14251}	{21.69588}	({56.82129})				
	[0.12945]	[0.51711]	[0.03100]	[0.03215]	[0.00000]	[0.00000]		[0.00000]	[0.00002]	[0.00700]

Note: t-statistics in {}, significance levels in [], and $\chi 2$ test statistics value in ({}). A Chi-square ($\chi 2$) test is used to test $(\alpha + \beta)$* equal to one. LF is the log likelihood function value and Ku the kurtosis of the residuals. Sk is the skewness of the residuals, and Q(30) is the Ljung-Box statistic serial correlation of the lags in the residuals. Ku, Sk, and Q(30) statistics are calculated from models different from those reported in Tables 2 and 5

Table 6 Panel A—Predictability Test Summary Statistics for Latin America Indexes and Latin American Emerging Markets, Based on Ljung-Box Q-Statistics Weekly Returns, 1988-98 (U.S.$)

	D - W	Autocorrelations Order				Ljung - Box Statistics		
Index	Statistics	First	Second	Third	Fourth	# of Lags	Q Value	Significance Level
LATIN AMERICA	1.9813	-0.01**	-0.013**	0.0182	0.0583	30	34.0234	0.2001
493 Observations						60	58.0866	0.4721
						90	85.8203	0.5459
Argentina	1.8923	0.0503**	0.046**	0.0691	-0.0426	30	58.0877*	0.0003
493 Observations						60	81.0113**	0.0161
						90	115.8392**	0.0176
Brazil	2.0039	-0.004**	0.019**	0.021	0.0019	30	36.4972	0.1595
493 Observations						60	58.3180	0.5006
						90	81.2105	0.7093
Chile	2.0034	-0.01**	-0.01**	-0.0233	0.0134	30	23.2323	0.6725
493 Observations						60	60.7284	0.3431
						90	86.8913	0.4832
Colombia	2.0343	-0.03**	0.113	0.03754	0.06968	30	59.0957*	0.0008
493 Observations						60	104.6584*	0.0002
						90	161.1667*	0.0001
Mexico	1.9847	0.003**	-0.013**	-0.0506	0.08091	30	24.0316	0.6799
493 Observations						60	54.3834	0.6106
						90	72.1261	0.8899
Peru	2.0474	-0.033**	0.034**	-0.0043	0.07501	15	17.3354	0.1844
284 Observations						30	44.6938**	0.0237
						45	59.9758**	0.0443
Venezuela	1.9697	0.0132**	-0.015**	-0.085	0.02547	30	28.5660	0.4348
493 Observations						60	55.9367	0.5524
						90	84.0478	0.5995

Note: The Ljung-Box statistics jointly test for the presence of autocorrelations with the significance levels given in the last column. The ** denotes a significant coefficient at the five percent level for the individual autocorrelations based on the t-test

* Significant at the 1 percent level for number of lags
** Significant at the 5 percent level for number of lags
*** Significant at the 10 percent level for number of lags

Table 6 Panel B—Predictability Test Summary Statistics for Latin America Indexes and Latin American Emerging Markets. Based on Ljung-Box Q-Statistics Weekly Returns, 1988-98 (Local Currency)

	D - W	Autocorrelations Order				Ljung - Box Statistics		
Index	Statistics	First	Second	Third	Fourth	# of Lags	Q Value	Significance Level
Argentina	2.00663	-0.0053**	-0.0051**	0.02151	-0.0122	30	36.0675	0.11383
493 Observations						60	82.8283**	0.01434
						90	115.7151**	0.02147
Brazil	1.99996	-0.0001**	0.0003**	-0.01641	-0.01824	30	1.6012	1.0000
493 Observations						60	2.4229	1.0000
						90	2.9906	1.0000
Chile	1.97222	-0.0009**	-0.0521**	-0.00268	0.001267	30	24.7644	0.64062
493 Observations						60	62.2055	0.32889
						90	90.6125	0.40316
Colombia	1.97008	0.01**	0.0081	-0.05816	-0.02549	30	54.4245*	0.00135
493 Observations						60	92.4275*	0.00208
						90	140.5577*	0.00024
Mexico	2.02879	-0.0172**	0.0136**	-0.00786	0.061074	30	33.0483	0.1607
493 Observations						60	68.4081	0.12353
						90	98.5599	0.16729
Peru	2.03201	-0.0335**	-0.0112**	0.01421	0.06649	15	13.5655	0.40514
284 Observations						30	40.0293***	0.065732
						45	50.6714	0.19668
Venezuela	1.84123	0.07287**	-0.0491**	-0.10526	-0.03221	30	27.341	0.49975
493 Observations						60	54.1591	0.61887
						90	79.3337	0.73412

Note: The Ljung-Box statistics jointly test for the presence of autocorrelations with the significance levels given in the last column. The ** denotes a significant coefficient at the five percent level for the individual autocorrelations based on the t-test

* Significant at the 1 percent level for number of lags

** Significant at the 5 percent level for number of lags

*** Significant at the 10 percent level for number of lags at the ten percent level, with Brazil and Chile almost significant at this level. A significant time-varying risk premium exists in these markets, with investors compensated with higher returns for bearing higher risk. Excluding Venezuela, which shows no ARCH/GARCH effects, only Peru appears to have no time-varying risk premiums. Consistent with the earlier findings of the Jarque-Bera test for normality of returns, residual kurtosis exists in all markets (Ku), with thicker tails than in a normal distribution. The Ljung-Box statistic [Q(30)] indicates the presence of serial correlation at the one percent level in the test residuals for Argentina, Colombia, and Peru.

The persistence of shocks to volatility is indefinite in conditioning future variance in the GARCH-M model if ($\alpha + \beta$) equals one (Engle and Bollerslev, 1986). Moreover, if ($\alpha + \beta$) is greater (smaller) than one, then the response function of volatility increases (decreases or decays) with time (Chou, 1988). In the present study, Brazil is the only market for which ($\alpha + \beta$) is greater than (but insignificantly different from) one. In Brazil, shocks to volatility may be permanent, implying that the conditional variance is nonstationary and that volatility movement affects stock prices.[6]

For the remaining markets, the persistence measure is less than unity, implying that shocks decay with time. Chile, for example, has a response function decay rate of 0.787 per week, such that after one year the proportion of shock that remains is negligible at 0.0000039, i.e., $(0.787)^{52}$. The proportion of shock that remains in the case of the Latin America index after one year is about 1.44 percent of the initial general, the same predictability results are obtained whether using U.S. dollars or local currency returns and autocorrelation or Ljung-Box statistics.

The Lo and MacKinlay (1988) results (Z-statistics adjusted for heteroskedasticity for a two, four, eight, 16, and 32 week holding period)[7] show that for U.S. dollars returns the LA index seems predictable for four, eight, and 16 week holding periods at 5 percent significance (Table 7, Panel A). Also, Colombia seems predictable for 8, 16, and 32 week holding periods at 5 percent significance (or lower), Chile for two, four, eight, and 16 weeks at 5 percent (or lower), and Venezuela at eight, 16, and 32 weeks at 5 percent or higher (Table 7, Panel A). Lo and MacKinlay also show that predictability seems to be more pronounced in local currency (Table 7, Panel B), in line with previous findings that predictability is more likely to be influenced by local information. In local currency, Brazil and Colombia seem predictable for two, four, eight, 16, and 32 week holding periods (at different significance levels). Also, Chile seems predictable for two, four, and eight weeks, and Venezuela for eight, 16, and

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[6] A significant impact of volatility on the stock prices can occur only if a shock to volatility persists over a long time (Poterba and Summers, 1986).

[7] Urrutia (1995), points out that computations of larger variance ratios (i.e., 48 or higher) are not appropriate and would probably yield spurious results considering the changing nature of the emerging markets.

32 weeks. These results are in line with Claessens, Dasgupta, and Glen's (1995) predictability results using 1976-1992 monthly returns and Harvey (1993) who finds emerging markets to be highly predictable.[8]

The nonparametric runs test results for weak form efficiency in U.S. dollars and local currency are shown in Table 8, Panels A and B. The Z-statistics indicate that the hypothesis of independence is decisively rejected for all cases, suggesting that Latin American equity markets are weak form inefficient. These results contrast with Urrutia (1995) who found four Latin American markets to be weak form efficient.

The performance of the model's predictive ability is applied to the last two years (104 weeks) of the data set with the results shown in Table 9, Panel A for U.S. dollars and Panel B for local currency.[9] The ARCH/GARCH model's predictive ability is good, as the squared forecast error means are significant throughout. The ability of ARCH models to provide good estimates of returns' volatility is well documented, and these results are consistent with that literature.[10]

Overall, the rejection of weak form efficiency and the predictability of the markets studied, especially in local currency, suggest that domestic investors could detect patterns in stock price, develop trading strategies, and earn abnormal returns. The caveat, however, is that in emerging markets, the appearance of profitable trading strategies might be due to other factors, such as time-varying risk premia (as found in Table 5). Also, the presence of autocorrelation in Latin American markets may be due to the rapid pace of growth of their economy and capital markets, rather than evidence against market efficiency.[11] Finally the return for the LA index is stable and predictable. Of course, the stability and predictability of the LA index may be due to the fact that Mexico and Argentina comprise 44 percent of the index. It is conceivable that foreign investors are concerned with Latin America as a region rather than a set of competing investment opportunities represented by the indices of individual countries. In that case, the fact that the LA index returns are stable and predictable has important portfolio implications.

[8] Variance-ratios larger than one suggest positive autocorrelation. Our results tend to agree with Lo and MacKinlay (1988), Poterba and Summers (1988), and Urrutia (1995).

[9] In this test, the model's predictions are made for the last two years of the existing data set and compared to the actual data for that period.

[10] Akgiray (1989) notes that the predictive capabilities of the ARCH and GARCH models constitute further evidence as to their overall usefulness as practical models of stock returns. Many studies, including Bollerslev (1987), Nelson (1991), and Glosten, Jagannathan, and Runkle (1993), show that the parameters of a variety of different ARCH models are highly significant.

[11] Lucas (1978) states that the existence of autocorrelation in financial markets does not necessarily imply market inefficiency.

Table 7 Panel A—Predictability Test Summary Statistics for Latin America Indexes and Latin American Emerging Markets. Based on Lo and MacKinlay Test, Weekly Returns, 1988-98 (U.S. $)

INDEX		V(2)	V(4)	V(8)	V16)	V(32)
Latin America		1.07745	1.26351**	1.460201**	1.62645**	1.28030
493 0bservations	Z(q)	1.71796	2.06312	2.23629	2.1246	0.61260
	SL	0.28128	0.03910	0.02533	0.03362	0.54014
Argentina		1.01715	1.08552	1.10296	1.05785	1.07290
493 0bservations	Z(q)	0.38041	0.69250	0.65113	0.19620	0.15780
	SL	0.70364	0.48862	0.51497	0.84446	0.87461
Brazil		1.01372	1.04905	1.08688	0.99861	0.72939
493 0bservations	Z(q)	0.30433	0.38408	0.47726	-0.00473	-0.58583
	SL	0.76088	0.70092	0.63318	0.99623	0.55799
Colombia		1.08641***	1.22022***	1.50197*	1.82952*	2.30621*
493 0bservations	Z(q)	1.91670	1.73970	2.75551	2.81320	2.82773
	SL	0.05528	0.08191	0.00587	0.00491	0.00469
Chile		1.09933**	1.39396*	1.72221*	1.74484**	1.51122
493 0bservations	Z(q)	2.20570	3.08459	3.96840	2.52639	1.10691
	SL	0.02740	0.00204	0.00007	0.01152	0.26834
Mexico		1.19717*	1.50031*	1.82354*	2.19844*	1.94549**
493 0bservations	Z(q)	4.37190	3.91860	4.52400	4.39076	2.04680
	SL	0.00001	0.00138	0.00001	0.00001	0.04068
Peru		1.03970	1.16755	1.32735	1.17394	0.72951
284 Observations	Z(q)	0.66970	0.99519	1.36760	0.44860	-0.44531
	SL	0.50305	0.31754	0.17144	0.65372	0.65610
Venezuela		1.06893	1.15749	1.39152**	1.65509**	1.75834***
493 0bservations	Z(q)	1.52830	1.23302	2.15080	2.22167	1.64190
	SL	0.12644	0.21757	0.03149	0.02631	0.10061

Final Conclusions and Comments

This study examines the stability, volatility, risk premiums, and persistence of shocks to volatility in the exchange-converted U.S. dollar returns of equities in Argentina, Brazil, Chile, Columbia, Mexico, Peru, Venezuela, and Latin America index using IFC weekly data within the 1988-98 period. It also examines the predictability of these markets using returns in both U.S. dollars and local currency. Box-Jenkins (1976), GARCH (q, p)-M, Ljung-Box, Lo and MacKinlay (1988), and nonparametric runs test methods are used to conduct the investigation.

All markets except Mexico, Peru, and Venezuela have time-varying risk premiums, indicative of risk aversion, with Chile having the highest Sharpe ratio. All markets except Venezuela have ARCH/GARCH effects. Venezuela seems to be the best market for gains from diversification, because it has the lowest cross-correlations with all other markets. All markets have residual kurtosis or fat tails, and Argentina, Colombia, and Peru have serial correlation. Shocks to volatility are persistent only in Brazil, with the shocks decaying in other markets to the point where effects are fairly negligible in one year or less. The predictability test results are mixed, with predictability pattern more pronounced when using local currency.

Table 7 Panel B—Predictability Test Summary Statistics for Latin America Indexes and Latin American Emerging Markets. Based on Lo and MacKinlay Test, Weekly Returns, 1988-98 (Local Currency)

INDEX		V(2)	V(4)	V(8)	V16)	V(32)
Argentina		1.0329	1.10323	1.14343	1.13965	1.18099
493 0bs	Z(q)	0.72981	0.25277	0.78795	0.47363	0.3918
	SL	0.46551	0.80045	0.43073	0.63576	0.6952
Brazil		0.83639*	0.70683**	0.60673**	0.48185***	0.33741
493 0bs	Z(q)	-3.629	-2.3435	-2.1604	-1.7573	-1.43434
	SL	0.00028	0.0191	0.03074	0.07887	0.15148
Colombia		1.10054**	1.26902**	1.56872*	1.86195*	2.06343**
493 0bs	Z(q)	2.23	2.1083	3.0896	2.9234	2.3013
	SL	0.02575	0.035	0.002	0.00346	0.02137
Chile		1.09698**	1.32113**	1.54433*	1.42259	1.33036
493 0bs	Z(q)	2.15169	2.51433	2.99034	1.43323	0.71539
	SL	0.03142	0.01193	0.00397	0.15179	0.47437
Mexico		1.067996	1.170485	1.164532	1.158687	1.00728
493 0bs	Z(q)	1.5084	1.3349	0.9038	0.5383	0.01576
	SL	0.131452	0.181909	0.366101	0.59037	0.987426
Peru		1.04981	1.15268	1.31067	1.14595	0.73123
284 Observations	Z(q)	0.8384	0.9076	1.2936	0.3754	-0.4416
	SL	0.40181	0.36409	0.1958	0.70736	0.65878
Venezuela		1.07198	1.17337	1.46325*	1.92202*	2.08513**
493 0bs	Z(q)	1.5965	1.3591	2.5474	3.1277	2.3483
	SL	0.11038	0.17412	0.01085	0.00176	0.01886

Note: The variance ratio test based on Lo and MacKinley(1988) is consistent under heteroskedasticity. Under the random walk hypothesis, which assumes that returns are i.i.d across time, return variance increases linearly with the length of holding period. Deviations indicate rejection of the random walk hypothesis and provide evidence that returns are predictable. Calculation are for "q" week holding period. Z(q) test statistics have been adjusted for heteroskedasticity. SL denotes the significance level

* Significant at the 1 percent level
** Significant at the 5 percent level
*** Significant at the 10 percent level

In general, Latin American emerging markets are stable, have volatility clustering with shocks that decay with time, and exhibit time-varying risk premiums. These emerging markets are, to some extent, predictable.

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Table 8—Runs Test, Summary Statistics for Latin American Emerging Markets. Weekly Returns, 1988-98

INDEX	N	M	E(M)	δ (M)	Z	Significance Level
Panel A: U.S. $						
Latin America	493	224	328.33	9.345	-11.164*	0.0000
Argentina	493	241	328.33	9.345	-9.345*	0.0000
Brazil	493	233	328.33	9.345	-10.201*	0.0000
Chili	493	216	328.33	9.345	-12.02*	0.0000
Colombia	493	199	328.33	9.345	-13.839*	0.0000
Mexico	493	211	328.33	9.345	-12.555*	0.0000
Peru	284	138	189	7.083	-7.200*	0.0000
Venezuela	493	216	328.33	9.345	-12.02*	0.0000
Panel B: Local Currency	N	M	E(M)	δ (M)	Z	Significance Level
Argentina	493	223	328.33	9.345	-11.271*	0.0000
Brazil	493	207	328.33	9.345	-12.983*	0.0000
Chili	493	188	328.33	9.345	-15.017*	0.0000
Colombia	493	189	328.33	9.345	-14.91*	0.0000
Mexico	493	210	328.33	9.345	-12.662*	0.0000
Peru	284	134	189	7.083	-7.765*	0.0000
Venezuela	493	212	328.33	9.345	-12.448*	0.0000

Note: N = total number of observations, M= actual number of runs, E(M) = (2N-1)/3, expected number of runs. δ (M)=$[(16N-29)/90]^{1/2}$, * significant at 1% level, Z=(M-E(M)) / δ(M)

Table 9—Performance Summary Statistics for Post Sample Predictions for Latin America Index and Latin American Emerging Markets, 19960531- 19980605 (104 Weekly Observations) Weekly Returns

Index	Obs	Mean of Squared Forecast Errors	Std Error	t-stat	Minimum	Maximum
Panel A: U.S. $						
Latin America	104	0.0010187	0.0030440	3.4127000	0.0000000	0.0253240
Argentina	104	0.0015592	0.0036903	4.3088000	0.0000002	0.0252276
Brazil	104	0.0021284	0.0066048	3.2862970	0.0000007	0.0615550
Chile	104	0.0006268	0.0020097	3.1806550	0.0000000	0.0200666
Colombia	104	0.0007536	0.0014794	5.1951140	0.0000001	0.0089716
Mexico	104	0.0011602	0.0024516	4.8260200	0.0000001	0.0187980
Peru	104	0.0006787	0.0012468	5.5511380	0.0000016	0.0067310
Venezuela	104	0.0021747	0.0042166	5.2596300	0.0000001	0.0296310
Panel B: Local Currency						
Argentina	104	0.0018245	0.0045232	4.1135700	0.0000002	0.0311882
Brazil	104	0.0021178	0.0065194	3.3128400	0.0000003	0.0607467
Chile	104	0.0005146	0.0010401	5.0458270	0.0000000	0.0092606
Colombia	104	0.0007113	0.0015091	4.8064500	0.0000000	0.0098017
Mexico	104	0.0008105	0.0016568	4.9885400	0.0000005	0.0146167
Peru	104	0.0006577	0.0011834	5.6680090	0.0000000	0.0065821
Venezuela	104	0.0020665	0.0038552	5.4663200	0.0000000	0.0250964

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