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Common Volatility across Latin American Foreign Exchange Markets

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Abstract:

This paper uses high frequency exchange rate data for a group of twelve Latin American countries to analyze volatility comovements. Particular interest is posed on understanding the existence of a common volatility process during the 1994–2005 period. The analysis relies on bivariate common factor models. We test for second-order common features using the common ARCH-feature methodology developed by Engle and Kozicki (1993). Overall, the results of this paper indicate that while most currencies display evidence of time-varying variance, the volatility movements in the Latin American foreign exchange markets seems to be mainly country specific. Only a few markets show evidence of a common volatility process.

SHSU ECONOMICS WORKING PAPER

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Key words: Common features, Common ARCH, Latin America, exchange rates

JEL Codes: F31 – Foreign Exchange

F36 – Financial Aspects of Economic Integration

G15 – International Financial Markets

1. INTRODUCTION

Since the 1990s, Latin American and Caribbean countries have implemented a series of significant policy changes and structural reforms. Such reforms, mandated by the International Monetary Fund (IMF), included drastic fiscal restraints, financial and trade liberalization, deregulation of government-owned firms, and liberalization of exchange rate regimes.[i] Although macroeconomic policy coordination was not formalized as an agenda, these changes have led to convergence in macroeconomic policies and to an increase in the interdependence of both trade and financial markets. As a result, economic policies and developments in one country have the potential to impact the whole region.

Given this convergence, exchange rates assume a particular important role. Exchange rate movements in one country can affect sales, profit forecasts, capital budgeting plans, and the value of international investments in a whole host of countries that trade with one another. Therefore, exchange rate developments in one country could significantly impact the region's economic stability. In this article, we investigate the dynamics and cross-country relationships among currencies in Latin America. More specifically, we focus on the existence of a common volatility process in Latin American exchange rates, and ask whether intracurrency variability is dominated common regional (or global) factors. That is, we analyze whether there are common factors driving volatility across these foreign exchange markets, or whether the mechanism driving volatility is market specific.[ii]

Furthermore, information about a common volatility process is useful in order to assess the extent of currency risks taken by investors within and outside the region.

Moreover, identifying a common volatility process is of interest given, in the past few years, that there has been an effort to consolidate and increase the market for derivative trading within Latin America. Indeed, there are already several securities exchanges in the region that trade derivative contracts, while over-the-counter derivative markets are emerging domestically.[iii] Any risk reduction through the identification of intracurrency relationships would be beneficial. Thus, the finding that these currencies exhibit a common volatility process could be useful information in the creation of cross-hedging policies based on derivatives (e.g., FX swaps).

To date, there are few extant studies on the properties of high frequency exchange rates within Latin America. Those that have been undertaken typically addressed the existence of regional comovements in other macroeconomic variables (see, for example, Edwards and Susmel, 2001, 2003; Escaith *et al.*, 2002; Hecq, 2002; Loayza *et al.*, 1999). Whilst studies examining exchange rate movements have focused on market efficiency and long-run properties of official and/or parallel foreign currency markets (Diamandis, 2003).

Based on a factor ARCH model, we investigate the existence of common factors driving intracurrency variability using an application of Engle and Kozicki's (1993) common features methodology. This methodology is a generalization of the concept of cointegration, and is based around the principle that if two series exhibit a feature individually but a linear combination of the two series does not exhibit the feature, then commonality exists. Thus we first test each currency for time dependent variance and then we form bivariate portfolios and test them for common volatility. In summary of the results below, whilst most currencies display evidence of time-varying variance, the volatility movements in Latin American foreign exchange markets seem to be mainly country specific. That is, only a few markets show evidence of a common volatility process.

The paper is organized as follows. Section 2 discusses the theoretical background and econometric methodology. In Section 3 we describe the data and the stochastic properties of high frequency exchange rates in Latin America. In Section 4 we use daily and weekly data for the 1994–2005 period to test for common volatility processes among foreign exchange markets in Latin America. Section 5 presents a summary and concluding remarks.

2. BACKGROUND THEORY AND ECONOMETRIC METHODOLOGY

The research on common features was born out of an academic interest to analyze, within a multivariate framework, whether time-series variables shared certain features. Engle and Kozicki (1993) generalized the concept of cointegration and developed a statistical test for the hypothesis that a feature of one series is common to other series. Such a feature would be common if there is a linear combination of the series for which the feature no longer exists.[iv]

The theoretical and econometric developments on cointegration have been widely applied in the literature. In contrast, the concept of common volatility is less known. Some of the most important applications of the common feature methodology in foreign exchange markets is the analysis of volatility comovements (see Alexander, 1995a). In this case, we can identify the direction of volatility comovements when responding to a common factor. Therefore, the analysis can highlight whether an individual can offset the risk from a position in one currency by taking a position in another (across market risk diversification). This hedging could be possible if the exchange rates share some common volatility. In this context, an investor could diversify by forming time invariant variance portfolios. Additionally, the amount and types of existing common features are indicators of the degree of market integration. The existence of common ARCH factors could be the response to global or regional factors affecting intracurrency variability.

The common volatility approach to the common feature testing is based on factor-ARCH structure models such as those proposed by Engle (1987) and Diebold and Nerlove (1989). In this type of model, asset prices are driven by a small number of latent variables, called factors, and by idiosyncratic disturbances. The latent variables have specific characteristics or features that influence the observables and give them this feature. This specification allows for a more tractable system of smaller dimension (Engle and Marcucci 2002, 2006).

The methodology for common volatility is based on the result that two stationary autoregressive conditional heteroscedastic time series have a common ARCH factor if and only if there exists a "no-ARCH" linear combination. The factor model specifies a covariance matrix having the property of a linear combination with "no ARCH." That is, there is a linear combination of the two series that does not display conditional heteroscedasticity. Suppose that returns on assets denominated in two Latin American currencies, denoted by x_{1t} and x_{2t}, have the following properties:

$$x_{1t} = f_{1t} + \eta_{1t} \quad \text{where} \quad f_{1t} / I_t \sim d(0, h_t^2) \tag{1}$$

and

$$x_{2t} = f_{2t} + \eta_{2t} \quad \text{where} \quad f_{2t} / I_t \sim d(0, k_t^2) \tag{2}$$

Where I_t denotes the information set available to economic agents at time t and η_{1t} and η_{2t} are mutually independent homoscedastic error components (the idiosyncratic components). Also, both h_t^2 and k_t^2 are time varying and follow an ARCH process. Now, consider a portfolio $y_t(\lambda) = x_{1t} + \lambda x_{2t}$. The variance of this portfolio is:

$$V_t(y_t(\lambda)) = h_t^2 + \lambda^2 k_t^2 + 2\lambda Cov_t(f_{1t}, f_{2t}) + (\sigma_1^2 + \lambda^2 \sigma_2^2) \qquad (3)$$

Where $(\sigma_1^2 + \lambda^2 \sigma_2^2)$ is constant. The variance of this portfolio $V_t(y_t(\lambda))$ would not display ARCH if and only if $f_{1t} = -\lambda f_{2t}$. In this case $h_t^2 = \lambda^2 k_t^2$ and $Cov_t(f_{1t}, f_{2t}) = -\lambda k_t^2$, in which case x_{1t} and x_{2t} have the common ARCH factor f_{2t}.

An investor with assets denominated in currency x_{1t} and x_{2t} could hedge her/his investment if both currencies share a common volatility process. In this case, with a scale factor λ, she/he can reduce the risk of a portfolio to $V_t(y_t(\lambda)) = (\sigma_1^2 + \lambda^2 \sigma_2^2)$. From a more general point of view, if both currencies share a common volatility process, it is also an indicator of integration among the countries. These two countries are responding to similar factors that cause volatility in their foreign exchange market.

The sign of λ determines the relationship between the currency returns corresponding to a common conditionally heteroscedastic factor. A negative λ suggests that changes in the volatility process are generally in the same direction. On the other hand, if the changes are in opposite directions, a positive coefficient allows the individual fluctuations to offset one another (see Alexander, 1995 a,b, Engle and Susmel, 1993).

The application of the common volatility methodology implies that we need to identify the presence of ARCH in the second moment of each series and find linear combinations that do not have ARCH. Following the literature on common ARCH, we conduct the test in three steps. First, we test for univariate ARCH factors in each currency return. We use squared currency returns (x_t^2) as a proxy of the realized volatility.[v] We estimate Engle's (1982) LM test, which is distributed as χ^2 with degrees of freedom equal to the number of over-identifying restrictions. Each squared currency return is regressed on a constant and lags of its own. We test the null hypothesis of "no ARCH" and the critical value is obtained by multiplying the uncentered R^2 by the sample size T (TR^2).

In the second step, we conduct a multivariate ARCH test for all squared currency returns. This multivariate ARCH test is conducted by regressing each squared currency return on a constant, and two information sets containing their own lags and lags of other squared currency returns. The first information set contains data for North America, Central America and the Caribbean (MARCH-NC), and the other contains lags of South American countries (MARCH-SA).[vi] The idea is to identify whether other currencies in the region are able to explain the volatility process in each country.

From the previous two steps, we take all series that are found to have significant ARCH and include them in the common volatility test. Series with "no ARCH" are not included in the test. Including series with no ARCH effect could be misleading in several ways. When testing for common volatility we are testing for the null hypothesis of "common volatility" or "no ARCH" in a linear combination of two currency returns. Thus, if one of the series does not have a time-dependent variance ("no ARCH"), then a linear combination with another series that possesses the ARCH feature might give false results, yielding a critical value that implies a failure to reject the null hypothesis and incorrectly conclude that both series have common volatility.[vii]

Finally, we take all those series for which we obtained significant ARCH and form bivariate portfolios of the form $y_t(\lambda) = x_{1t} + \lambda x_{2t}$. Following Engle and Kozicki (1993), we regress the squared portfolio on a constant and a multivariate information set Z_t that contains lags of each squared currency return and lagged cross products of both currency returns.[viii] Here we are testing for the null hypothesis of common ARCH. To find such portfolios, we minimize the TR^2 obtained from the auxiliary regression over the scale factor λ (cofeature parameter). This is a GMM (Hansen 1982) type of estimation, which follows a χ^2 distribution with degrees of freedom equal to the number of over-identifying restrictions.

The minimization is conducted through a quasi-Newton optimization method, BFGS, and through a grid search with inclusive bounds for λ of –100 and 100 and in a 0.01 sequence.[ix] We expanded the interval for the grid search whenever the minimization resulted in λ equaling one of the bounds. In Figure 1 we show the case of a bivariate portfolio consisting of the Chilean peso and Colombian peso, where Chile's coefficient is normalized to be one. As we can see from the graph, the minimum is well defined and so is the case for most bivariate portfolios.

Whenever the minimum TR^2 exceeds the critical value, we reject the null hypothesis of common volatility. Conversely, when we fail to reject the null hypothesis we conclude that the portfolio no longer displays ARCH and that the currency returns share a common volatility process. From this step we identify all portfolios that are not correlated in the squares with any information included in Z_t. Such portfolios are the candidates to be "no ARCH" portfolios, or portfolios that share a common ARCH factor.

3. DATA DESCRIPTION AND DESCRIPTIVE STATISTICS

In this paper, we use data for twelve Latin-American currencies. The sample period begins in January 3, 1994, and ends in February 8, 2005, for a total of 2,897 daily and 578 weekly observations. The source of the data is Bloomberg's database and the sample contains the currencies of Argentina, Bolivia, Brazil, Colombia, Chile, The Dominican Republic, Guatemala, Mexico, Paraguay, Peru, Uruguay and, Venezuela, all *vis-à-vis* the U.S. dollar.[x] The first differences of the logarithm of the nominal exchange rates are used as currency returns.[xi]

The use of daily and weekly data is typical in this literature. Weekly data are often included to avoid the noisiness typically encountered in daily data and to avoid the "weekend effect." It also eliminates nonsynchronous trading and problems of short-term correlation. It is rather common to find weekly estimates based on Wednesday reports or using an average from "Thursday to Thursday" in which weekend data is excluded. We use both measures in our estimation. Because of space considerations and because the results do not change considerably, we only present the results based on Wednesday reports.

The focus of this paper is on data corresponding to the last decade because, during this period, the currencies of the sample have gradually moved towards more flexible exchange rate systems (i.e. Brazil, Chile, Colombia, Mexico, Peru). It is also important to note that the data on exchange rates used in this study pertains to the official market. For some currencies, there still might be significant foreign exchange traded in parallel markets, which coexist with the official market (see Diamandis, 2003).

Table 1 presents some summary statistics for the daily and weekly data. The general characteristics of the data are similar to that reported elsewhere for financial data, namely, a small mean dominated by a larger standard deviation, with evidence of a non-normal distribution. Of particular note, when examining both daily and weekly data, the largest standard deviations are found for Argentina, Brazil, Mexico, Dominican Republic, and Venezuela, while most notable cases of leptokurtosis were those of Argentina, Bolivia, Mexico, Paraguay, and Venezuela. Furthermore, the skewness parameter, which is of importance because it can capture the presence of a small number of large movements in any direction, are typically positive, indicating the presence of a few relatively large devaluations during the period. This is consistent with the tendency for the countries within our sample to practice policies oriented toward devaluation. As indicated by the Jarque–Bera statistic (JB), the null hypothesis of normality was rejected for most currency returns and, therefore, the unconditional distribution for all currency returns is non-normal. Finally, the Ljung-Box (LB) statistics suggest the presence of autocorrelation in both the mean and variance of our series.

4. COMMON VOLATILITY IN THE FOREIGN EXCHANGE MARKET

4.1 Daily Results

In testing for common volatility, we first explore the presence of ARCH factors in each currency return. To test for ARCH, we use a version of Engle's (1982) LM tests for the null hypothesis of "no ARCH" in which each squared currency return series is regressed on a constant and lags of itself. We use 1 to 4, 8, and 12 lags because increasing the lag length can capture the GARCH effects (Alexander, 1995a).

The results of univariate ARCH tests are reported in Table 2. This table reports the TR^2 statistics for the null hypothesis of no ARCH. The results strongly reveal the presence of time-varying volatility for each of the currencies except for the Venezuelan Bolivar. Increasing the lag used in univariate ARCH tests does not increase the significance of the effect for Venezuela. The TR^2 results for Argentina are small. Yet, they are significant so as to reject the null hypothesis of "no ARCH."

In the second step, we take all currency returns for which the LM test indicates the presence of ARCH and subject them to a multivariate ARCH test. The test is constructed by conducting a regression of each squared currency return on a constant and a multivariate information set. This information set contains lags of the squared return and squared returns of other countries' currencies. We use the two sets of information defined earlier in the text: MARCH-NCA and MARCH-SA. The goal is to find out if introducing other currencies as explanatory variables can capture ARCH.

The results are reported on the last four columns of Table 2. *F*-values obtained from a Wald test for the significance of exogenous variables are reported in parentheses. Whenever a currency increases the explanatory power of the test for other currencies, it suggests that it is a useful instrument for detecting ARCH. For most countries, except Venezuela, other Latin American countries help to explain the volatility process. In the case of Argentina, South American countries are helpful in detecting ARCH, while North and Central American countries are not. It is worth noting that the power of the test increases when we include other currencies for Colombia and Chile. Also, in the case of the Paraguayan currency, the Brazilian and Uruguayan currencies are helpful in detecting ARCH.[xii]

Subsequently, we conduct the test for common volatility for all possible bivariate portfolios, although Venezuela is excluded from the analysis because of the absence of time-varying variance (and hence there can be no common ARCH). However, when testing for common volatility for the whole period (1994-2005), no common ARCH is found. Therefore, for daily data, despite the evidence of conditioning effects between volatility as given by the MARCH test, there is a lack of evidence of a common volatility process within these foreign exchange markets. One plausible explanation for the lack of common ARCH in daily data is that such data might be too noisy to detect any common feature (see Alexander, 1995a,b and Engle and Susmel, 1993).

4.2 Weekly Results

We also make use of a sample of weekly data. The use of weekly data allows us to avoid the noisiness typically encountered in daily data. In this sample, as with daily data, the null hypothesis of "no ARCH" is rejected for most of the currency returns at the 5% level of confidence (see Table 3). Thus, most currencies pass the first test and are included in the test for common volatility. The last four panels of Table 3 present the estimates of the multivariate test. Again, the Venezuelan Bolivar did not pass any of the tests and as a result, this currency is not included in the tests for common volatility.

We then proceed to conduct the common volatility test for which Table 4 contains information on all of the portfolios that passed the test for common volatility. Most of the portfolios that passed the test were in relation to Argentina and Chile. In particular, to note some examples, the portfolio of Argentina and Uruguay displayed common conditional variance with a factor $\lambda = 0.84$. This suggests that the movements on the conditional volatility of both currencies are in opposite directions. On the other hand, Chile and Colombia share a common ARCH factor with a negative λ (-0.67), thus it moves in a similar direction, which weakens and strengthens in the same fashion.

Overall, the results of common volatility as indication of financial linkages are warranted for the case of Argentina and Uruguay. These two economies are highly integrated both financially and in terms of trade, as they are part of the Mercosur. Also, countries like Chile and Colombia have followed similar macroeconomic policies. They both are inflation targeters and they have followed similar exchange rate regime strategies.

5. SUMMARY AND CONCLUDING REMARKS

In this paper, we investigate the dynamics among Latin American countries in terms of foreign exchange market integration and volatility comovements using daily and weekly data for the 1994–2005 period. First, we examined time series properties of Latin American exchange rates. Several characteristic properties of major exchange rates, already documented in the literature, are also found for Latin America. Specifically, we find that at daily and weekly frequency, the exchange rates have an asymmetric non-normal distribution with higher probability in the tails relative to the normal distribution.

In order to test for any common volatility process in these foreign exchange markets, we apply a factor ARCH model and the methodology of Engle and Kozicki's (1993) common features principle. First, we tested each currency for time-dependent variance. Second, we formed bivariate portfolios and tested them for common volatility. Our results indicate that most of the currencies (with the exception of Venezuela) displayed time-varying variance. The absence of time varying variance in Venezuela might be a result of their foreign exchange practices. More specifically, in the last eight years, different exchange rate regimes have been applied in Venezuela: crawling band

(1996-2001), free floating (2002) and, since 2003, capital controls with a semi-fixed exchange rate (see Giner and Mendoza, 2003).

The results from daily and weekly data indicate that with a few exceptions, exchange rates in Latin America do not share a common volatility process. Thus, most countries' currency return variance is not driven contemporaneously by factors common to other currencies' volatility. It also may be that the common factors are too small (so as not to be detected) relative to the idiosyncratic components.

These results are similar to that reported elsewhere in the literature for financial variables. That is, for example, Edwards and Susmel (2003) (in the case of interest rates) and Edwards and Susmel (2001) (in the case of the stock market), find that during the 1990s, there is only weak evidence of volatility comovements across Latin American countries, and they do not support the existence of contagion. Similarly, Berg, *et al.* (2003) find that the degree of comovements of several financial variables, including the exchange rates, is not higher among Latin American countries than it is among other emerging markets.

Our findings have several implications. Most notably, the variances of each currency appear to be largely country specific. Therefore, intracurrency diversification within the region is not a straightforward strategy for portfolio risk reductions, and further analysis regarding properties of high frequency exchange rate data for Latin America must be carried out. On the other hand, this weak evidence of common volatility could be stemming from a variety of situations: i) capital controls may insulate countries from regional factors; ii) the significant foreign exchange traded in the black markets may limit findings of common volatility. It is possible that common volatility is more likely to be observed the black rather than in the official markets.

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REFERENCES

Alexander, C. (1995a) Common volatility in the foreign exchange market, *Applied Financial Economics,* **5**, 1–10.

Alexander, C. (1995b) Cofeatures in International Bond and Equity Markets, *University of Sussex Discussion Papers*: Ismacentre.

Anderson, H. and Vahid, F. (2005) Forecasting the Volatility of Australian Stock Returns: Do Common Factors Help? *The Australian National University, Working Papers in Economics and Econometrics*, WP 451.

Berg, A., Borenztein, E. and Mauro, P. (2003) Monetary Regime Options for Latin America, *Finance and Development,* 24–27.

Diamandis, P. (2003) Market Efficiency, Purchasing Power Parity, and the Official and Parallel Markets for Foreign Currency in Latin America, *International Review of Economics and Finance,* **12**, 89–110.

Diebold, F. and Nerlove, M. (1989) The Dynamics of Exchange Rate Volatility: A Multivariate Latent Factor ARCH Model, *Journal of Applied Econometrics,* **4**, 1–21.

Edwards, S. (1998) Capital Inflows in Latin America: A Stop-Go Story? *National Bureau of Economic Analysis* (NBER), Working Paper: 6441.

Edwards, S. (2003) Financial Instability in Latin America, *Journal of International Money and Finance,* **22,** 1095–1106.

Edwards, S. and Susmel, R. (2001) Volatility Dependence and Contagion in Emerging Equity Markets, *Journal of Development Economics*, **66**, 505-532.

Edwards, S. and Susmel, R. (2003) Interest Rate Volatility and Contagion in Emerging Markets: Evidence from the 1990s, *Review of Economics and Statistics,* **85**, 328–348.

Engle, R. (1982) Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of U.K. Inflation, *Econometrica,* **50**, 987–1008.

Engle, R. and Kozicki, S. (1993) Testing for Common Features (With Comments), *Journal of Business and Economic Statistics,* **4,** 369–395.

Engle, R. and Marcucci, J. (2002) Common Features: An Overview of Theory and Applications to Finance, University of California, San Diego, Manuscript.

Engle, R. and Marcucci, J. (2006) A Long-Run Pure Variance Common Features Model for the Common Volatilities of the Dow Jones, *Journal of Econometrics,* **132**, 7–42.

Engle, R. and Susmel, R. (1993) Common Volatility in International Equity Markets, *Journal of Business and Economic Statistics,* **11**, 167–176.

Escaith, H., Ghymers, C. and Studart, R. (2002) Regional Integration and the Issue of Choosing an Appropriate Exchange Rate Regime in Latin America, ECLAC, **14**.

Giner, I. and Mendoza, O. (2005) Foreign Exchange Intervention in Venezuela, Bank of International Settlements, BIS papers.

Hansen, L. P. (1982) Large Sample Properties of Generalized Method of Moments Estimators, *Econometrica,* **50**, 1023–1054.

Hecq, A. (2002) Common Cycles and Common Trends in Latin America, *Medium Econometrische Toepassingen,* **10,** 20–25.

Loayza, N., Lopez, H. and Ubide, A. (1999) Comovement and Macroeconomic Interdependence: Evidence for Latin America, East Asia and Europe, *Central Bank of Chile, Working Paper* 60.

Table 1 – Summary Statistics for Daily and Weekly Currency Returns (1994 –2005)

Country	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*LB*	*LBS*	*JB*
Argentina (d)	0.037**	1.054	14.63*	444.16*	115.71*	44.20*	0.000
Argentina (w)	0.002**	0.024	10.36*	154.58*	57.22*	27.41*	0.000
Bolivia (d)	0.020**	0.005	2.11*	230.97*	360.84*	348.75*	0.000
Bolivia (w)	0.001*	0.006	0.56*	200.59*	152.57*	142.97*	0.000
Brazil (d)	0.107*	0.977	0.31*	24.1*	383.12*	1341.9*	0.000
Brazil (w)	0.005*	0.028	1.64*	13.88*	341.59*	411.07*	0.000
Chile (d)	0.011	0.470	0.03*	7.22*	31.78*	374.95*	0.000
Chile (w)	0.0005*	0.010	-0.08	5.36*	28.33*	30.70*	0.000
Colombia (d)	0.037*	0.476	1.03*	15.88*	5.57*	229.69*	0.000
Colombia (w)	0.002*	0.010	0.62*	5.84*	40.35*	38.92*	0.000
Guatemala (d)	0.010*	0.205	0 .14*	18.30*	147.95*	124.37*	0.000
Guatemala (w)	0.0005*	0.005	0.76*	8.28*	20.22*	20.35*	0.000
Mexico (d)	0.044**	1.032	1.62*	102.35*	83.123*	1172.9*	0.000
Mexico (w)	0.002*	0.019	4.60*	43.62*	46.21*	124.56*	0.000
Paraguay (d)	0.043*	0.727	-2.78*	139.72*	79.79*	185.75*	0.000
Paraguay (w)	0.002*	0.012	0.82*	13.73*	24.15*	190.77*	0.000
Peru (d)	0.014*	0.287	0.99*	45.31*	75.63*	451.92*	0.000
Peru (w)	0.0007*	0.006	0.30*	11.04*	17.89*	122.15*	0.000
D. Republic (d)	0.023	1.028	0.59*	49.68*	106.5*	839.66*	0.000
D. Republic (w)	0.002	0.023	0.77*	27.52*	14.04**	84.01*	0.000
Uruguay (d)	0.059*	0.010	0.83*	77.36*	252.04*	1135.4*	0.000
Uruguay (w)	0.003*	0.016	0.09	27.38*	44.88*	652.2*	0.000
Venezuela (d)	0.099*	1.736	20.40*	619.65*	10.08	0.048*	0.000
Venezuela (w)	0.005*	0.038	8.883*	113.04*	5.44	0.059*	0.000

Note: *, ** and *** indicate 1%, 5% and 10% significance level. Currency returns are the % change in the log of exchange rates. Daily data is denoted by (d) and (w) refers to weekly data. LB is the Ljung Box test for serial correlation with 6 lags. LBS refer to the Ljung Box-Squared. Jarque-Bera Statistic, JB, reports the p-values for the test against the null hypothesis of a normal distribution.

Table 2 – TR^2 Statistics: ARCH Tests of Daily Dollar Return (1994–2005)

	TxR² ARCH Test						*Multivariate ARCH (MARCH)*			
Squared Returns	*ARCH (1)*	*ARCH (2)*	*ARCH (3)*	*ARCH (4)*	*ARCH (8)*	*ARCH (12)*	*MARCH-NCA(1)*	*MARCH-NCA(2)*	*MARCH-SA (1)*	*MARCH-SA (2)*
Argentina	12.90*	13.25*	40.67*	40.67**	48.03*	86.81*	6.67 (2.89)***	14.28 (1.66)	15.70* (6.81)*	16.67 (3.35)*
Bolivia	380.61*	529.38*	689.30*	697.82*	751.12*	833.28*	12.83* (4.17)*	293.74* (31.34)*	270.38* (20.18)*	294.38* (1.17)
Brazil	269.58*	293.38*	309.59*	309.49*	310.43*	310.07*	122.57* (50.67)*	530.38* (2.53)	406.06* (29.38)*	886.52* (16.48)*
Chile	453.01*	488.80*	511.01*	519.72*	534.87*	546.64*	405* (158.06)*	551.30* (103.41)*	516.03* (76.31)*	571.73* (42.98)*
Colombia	175.42*	222.48*	244.42*	253.43*	265.59*	271.65*	181.30* (71.90)*	279.30* (45.00)*	232.96* (26 .68)*	291.39* (17.34)*
Guatemala	206.06*	212.07*	215.51*	220.54*	241.10*	245.26*	207.45* (50.28)*	213.78* (31.65)*	176.52* (20.58)*	180.62* (12.59)*
Mexico	165.47*	554.81*	563.33*	629.15*	633.31*	667.34*	165.71* (10.31)*	555.21* (8.61)*	166.70* (8.02)*	666.84* (4.96)*
Paraguay	154.42*	159.10*	166.60*	166.56*	179.08*	179.42*	21.15* (13.70)*	159.49* (8.53)*	185.79* (6.49)*	424.56* (2.42)*
Peru	90.83*	109.11*	467.04*	471.26*	526.79*	539.23*	65.47* (23.07)*	109.52* (14.69)*	98.66* (11.08)*	118.29* (8.82)*
Dom. Republic	624.17*	625.34*	627.15*	635.68*	640.47*	646.10*	624.50* (21.00)*	625.97* (12.96)*	628.42* (8.67)*	120.77* (4.88)*
Uruguay	151.35*	609.74*	644.07*	644.28*	833.50*	880.91*	36.68* (13.58)*	610.30* (8.54)*	164.07* (7.86)*	627.15* (3.37)*
Venezuela	4.71**	4.71	4.71	4.71	4.75	4.78	4.8 (2.47)***	5.01 (1.50)	5.05 (1.82)	5.86 (1.34)
5% Conf. Value for $TR^2(\chi^2)$	3.84	5.99	7.81	9.49	15.51	21.03	9.49	15.51	15.51	26.30

Note: *,**, *** indicate 1%, 5% and 10% significance level. These are the TR^2 critical value for the null hypothesis of no ARCH. The TR^2 statistic for the ARCH test is generated from regressing the squared currency return on a constant and lags of own squares. The test distribution is χ^2 with degrees of freedom p = 1, 2, 3, 4, 8 and 12. (i.e. ARCH(p) indicates univariate ARCH with p lags). MARCH is an ARCH test with a multivariate information set. The test is conducted by regressing the squared currency return, on a constant, lag of its own and lags of other currency returns. The numbers in parenthesis give the Wald test statistic for the significance of exogenous variables.

Table 3 – TR^2 Statistics: ARCH Tests of Weekly Dollar Returns (1994–2005)

Squared Returns	*ARCH (1)*	*ARCH (2)*	*ARCH (3)*	*ARCH (4)*	*ARCH (8)*	*ARCH (12)*	*MARCH-NCA (1)*	*MARCH-NCA (2)*	*MARCH-SA (1)*	*MARCH-NCA (2)*
Argentina	29.71*	29.90*	29.86*	30.17*	30.57*	56.71*	3.93 (1.44)	4.07 (1.12)	31.25 * (0.69)	31.89* (0.69)
Bolivia	144.23*	188.69*	211.04*	224.11*	243.23*	246.97*	3.23 (0.76)	3.67 (0.60)	146.3* (0.65)	121.26* (0.54)
Brazil	233.79*	233.59*	234.51*	232.73	249.84*	241.43*	41.69* (12.32)*	42.27* (7.72)*	242* (2.83)*	252.43* (2.65)*
Chile	108.94*	110.10*	117.77*	118.20*	133.99*	134.62*	110* (34.09)*	128.3* (21.72)*	117.21* (14.46)*	121.46* (8.19)*
Colombia	102.79*	108.53*	112.22*	113.07*	118.21*	118.64*	96.11* (29.26)*	97.12* (17.24)*	106.28* (17.05)*	130.72* (8.38)*
Guatemala	83.15*	83.10 *	83.09*	83.37*	87.68*	88.41*	84.01* (22.59)*	84.49* (9.71)*	73.36* (15.05)*	82.53* (7.70)*
Mexico	114.25*	120.10*	129.80*	130.12*	145.95*	194.66*	114.56* (4.83)*	120.3* (2.80)*	37.70* (3.68)*	39.89* (2.65)*
Paraguay	106.03*	116.00*	123.36*	125.93*	134.02*	143.60*	44.47* (15.78)*	44.72* (9.51)*	111.6* (4.43)*	128.60* (2.35)*
Peru	141.83*	142.84*	148.16*	147.92*	148.27*	151.44*	58.25* (16.84)*	63.95* (12.04)*	149.19* (9.26)*	159* (2.92)*
D. Republic	48.62 *	48.65*	58.40*	65.97*	74.33*	90.73*	49.31* (8.35)*	49.70* (4.57)*	58.74* (3.83)*	60.92* (2.25)*
Uruguay	187.98*	200.44*	200.25*	217.27*	272.41*	289.80*	23.32* (8.91)*	23.49* (5.90)*	200.99* (1.70)***	229.92* (1.99)*
Venezuela	5.08*	5.08	5.10	5.11	5.17	5.28	5.15 (2.29)***	5.42 (1.37)	5.36 (2.41)*	6.15* (1.17)
5% C. Value (χ^2)	3.84	5.99	7.81	9.49	15.51	21.03	7.81	12.59	16.92	28.87

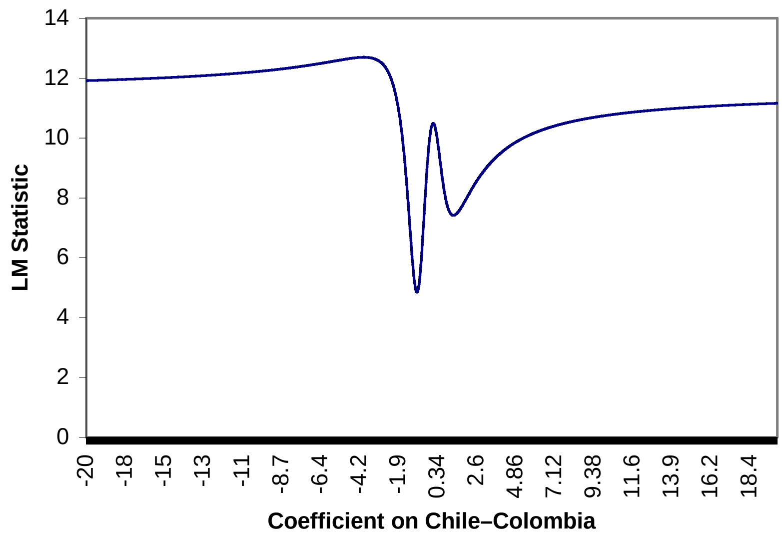
Note: *,**, *** indicate 1%, 5% and 10% significance level. These are the TR^2 critical value for the null hypothesis of no ARCH. The TR^2 statistic for the ARCH test is generated from regressing the squared currency return on a constant and lags of own squares. The test distribution is χ^2 with degrees of freedom p = 1, 2, 3, 4, 8 and 12. (i.e. ARCH(p) indicates univariate ARCH with p lags). MARCH is an ARCH test with a multivariate information set. The test is conducted by regressing the squared currency return, on a constant, lag of its own and lags of other currency returns. The numbers in parenthesis give the Wald test statistic for the significance of exogenous variables.

Table 4 – Common ARCH Feature Test for Weekly Data (1994–2005).

Countries	Min TR2	λ	ARCH (4)
Argentina/ Uruguay	***9.11***	***0.84***	***5.43***
Argentina/Colombia	6.08	0.25	3.01
Chile/Brazil	15.36	-0.05	10.82
Chile/Colombia	***8.86***	***-0.67***	***2.01***
Chile/Guatemala	16.37	-0.38	9.40
Chile/Peru	10.83	-0.7	5.46
Colombia/Guatemala	***13.68***	***0.34***	***4.15***
5% Confidence Value	21.03		9.49

Note: * Significant at the 5% level. Results are the minimum TR^2 of the regression of $y(\lambda) = (x_{1t} + \lambda x_{2t})^2$ on a constant and a multivariate information set Z_t (four lags of each currency (x_{1t} and x_{2t}), and four lags of cross products ($x_{1t} * x_{2t}$)). ARCH (4) is referred to an ARCH test of the portfolio $y(\lambda)$ on four own lags.

Figure 1 – LM Statistic: TR^2 Minimization over λ



Endnotes

[i] Many of these reforms were included in the Washington consensus (1990) as a response for the financial crises that the region underwent in the 1980s (see Edwards, 1998, 2003).

[ii] Common volatility could be driven by a number of factors including oil prices, policy coordination, etc. The existence of common volatility indicates that the manner in which the currencies evolve is closely related.

[iii] The largest derivatives exchanges in the region are located in Argentina (Mercado a Término of Buenos Aires [MATBA], Mercado a Término of Rosario [ROFEX]); Brazil (Bolsa de Mercadorias y Futuros [BM&F], BOVESPA index); and Mexico (Mexican market for derivatives [MexDer]). In addition, over-the-counter (OTC) exchange derivative markets exist in Chile and Peru.

[iv] Different features have been studied, examples are: seasonal components, non-linearities, serial correlation, structural breaks, kurtosis, skewness, and seasonality. For a complete literature review on different applications of the testing procedure, see the special edition of the Journal of Business and Economics Statistics, 11 (1993) and Journal of Econometrics, 132, 1 (2006), which cover theoretical and empirical advances on common features.

[v] We focus on the volatility process of the exchange rates and therefore do not model the mean of the process. Rather, we use the squared returns as a proxy of volatility. The financial literature has focused recently on high-frequency returns between period t−1 and t to obtain a consistent estimator of volatility for time t (by squaring the returns). This measure of volatility is what is known as "realized volatility" (see Anderson and Vahid, 2005).

[vi] MARCH-NCA contains lags of Mexico, Guatemala, and the Dominican Republic. On the other hand, MARCH-SA contains lags of Argentina, Bolivia, Brazil, Chile, Colombia, Paraguay, Peru, and Uruguay.

[vii] From Engle and Kozicki (1993), three axioms follow the common feature methodology: i) If x_{1t} has (does not have) the feature, then ax_{1t} with $a \neq 0$ will have (not have) the feature; ii) If neither x_{1t} nor x_{2t} have the feature, then a linear combination of them will not have the feature; and finally, iii) if x_{1t} does not have the feature and x_{2t} does have the feature, then $y = x_{1t} + x_{2t}$ will have the feature.

[viii] The criterion to determine the optimal number of lags is not formally specified in the literature. However, in this study we follow the convention by using four lags of currency 1, four lags of currency 2, and four lags of cross products.

[ix] BFGS stands for Broyden–Fletcher–Goldfarb–Shanno. Both methods were used as a check for robustness. The results using the two methods did not differ much; both led to similar conclusions. The grid search helped to determine if the minimum is well defined. In fact, when looking at all combination of currencies, we find that, in general the minimum is well defined for most currency pairs.

[x] Daily data corresponds to five days a week (weekends excluded). Initially we included 14 currencies but we excluded the Costa Rican and Nicaraguan currencies. The reason lies in that their returns were I(1) processes therefore not confirming the stationarity property. The sample for Argentina starts in 2001. Before 2001, its currency was pegged to the U.S. dollar. Most data comes from Bloomberg's' database but the data from Bolivia and the Dominican Republic, which come from their own central banks.

[xi] For the returns we use $x_t = [\log(e_t) - \log(e_{t-1})]*100$ where e_t is the exchange rate in day t and x_t denotes daily currency return. The log of the nominal exchange rates is expressed in foreign currency received for one U.S. dollar. The validity of this first-difference transformation in rendering the underlying series stationary is confirmed by the results of unit root tests using the ADF, DF-GLS and KPSS tests (not shown here).

[xii] We also conducted bivariate ARCH tests, but the results are not presented but available upon request. The results are in line with the conclusions obtained from the MARCH test.