Integration and Common Volatility across Latin American Foreign Exchange Markets

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Abstract

Using daily and weekly data for the 1994–2005 period, this paper investigates the linkages and the nature of the volatility process among foreign exchange markets in Latin America. This is achieved by testing for first- and second-order common features. Common features arise when the series exhibit comovements, i.e., when they are generated by common factors. Two types of features are sought: common stochastic trends and common ARCH factors. We employ cointegration analysis to test for common stochastic trends. The evidence suggests a pattern of integration among Latin American countries and across some subregional areas. In particular, most countries are cointegrated with the Brazilian real. However, this relationship holds for the mid and late 1990s and not for the early 2000s. To examine the issue of a common volatility process among the foreign exchange markets, we test for second-order common features using the common ARCH-feature methodology developed by Engle and Kozicki (1993). While most currencies display evidence of time-varying variance, the volatility movements in Latin American foreign exchange markets seems to be mainly country specific. It is found that only few markets show evidence of common volatility. Most of this common volatility is found in relation to the Chilean peso and the Brazilian real. This evidence seems to be stronger after the year 2001.

Keywords: Common features, common ARCH, exchange rates, cointegration, Latin America.

JEL Classification: F31 – Foreign Exchange
F36 – Financial Aspects of Economic Integration

1. Introduction

Since the 1990s, Latin America and the Caribbean 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 exchange rate regime changes.[1] Although macroeconomic policy coordination was not formalized as an agenda, the consequences of these changes have led to some convergence in macroeconomic policies and to an increase in the interdependence of both trade and financial markets.[2] As a result, economic policies and developments in one country can impact the whole region.

Take, for example, the case of exchange rates. 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 can significantly impact the region's political and economic stability. This paper contributes to the literature on the properties of exchange rates in Latin America. By investigating the cross-country relationships, and by studying the dynamics and interaction among currencies in the region, we increase the understanding of financial integration. In order to study such interactions, we focus on both the level of the currency and a measure of its volatility by testing for first- and second-order common features (common stochastic trends and common volatility).

When studying the dynamics and interactions of currencies in levels, we are interested in analyzing whether there is a long-run relationship among currencies in the region, thus we test for the existence of cointegration. Testing for cointegration in foreign exchange markets is fairly common in the literature (see Baillie and Bollerslev 1989, 1994; Hakkio and Rush 1989, 1991; Diebold et al. 1994; McDonald and Taylor 1989; Jeon and

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[1] During this period two countries in Latin America, El Salvador and Ecuador, gave up their currency to adopt the U.S. dollar. Other countries have moved towards a more flexible exchange rate system, as in the cases of Colombia, Mexico, Chile, and Brazil.

[2] For example, with respect to trade, intraregional exports among the sample of countries used in this paper have increased from 23.3% of total trade in 1990 to 32.1% of total trade in 2003. As of 2003, some of these countries have intraregional exports that are more than 40% of their total exports: Bolivia (59.5%), Guatemala (43.3%), Nicaragua (43.8%), Paraguay (64.7%), and Uruguay (40.8%). (Data source: ECLAC and U.N. Comtrade).

Lee 2002; Lee 2003; and Emmanuel 2005, among others). The aim is to ascertain if there is a common force that determines the long-run movements in a group of exchange rates. However, these techniques have not been applied to Latin American exchange rates.

In this paper, tests for cointegration are conducted using the techniques developed by Johansen (1991, 1995). First, we test for cointegration in the entire set of countries over the 1994–2005 period, and then analyze two subperiods. The first subperiod is from 1994–2000 and the second is 2001–2005. We chose to conduct separate analysis for the 1994–2000 period because there were several financial crises in the region, and many of the currencies were under considerable pressure. Moreover, during the year 1999, two countries allowed their currencies to be completely flexible and announced their intentions of not intervening in the foreign exchange market (such is the case of Chile and Colombia). Thus, we analyze the whole period and these two subperiods to track whether patterns in the cointegrating relationships changed over the time period considered.

In addition, we group Latin American currencies according to existing trade agreements. Understanding the relationship between the currencies in these trade blocs is of interest given the U.S. Congress' recent approval of the Central American Free Trade Agreement (CAFTA).[3] Identifying currencies driving the long-run equilibrium in the region is of interest because it has implications for the possibilities of cross-country hedging of foreign exchange risk. In addition, it can shed light on the likely impacts of more trade and financial integration in the region.

The second approach to analyzing financial linkages as they pertain to foreign exchange is to test for integration in terms of volatility. This paper analyzes whether there are common factors that drive volatility in these markets. The majority of studies explaining the cross-country dynamics of exchange rate volatility are with respect to the world's major currencies. However, few studies focus on whether there are common volatility processes driving the foreign exchange market in emerging economies. This paper

[3] CAFTA was approved in July 2005 and signed into law on August 2, 2005. It is a comprehensive trade agreement between Costa Rica, the Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, and the United States. CAFTA aims to reduce barriers to trade among the signers of the agreement. It also requires reforms of the domestic legal and business environment for the Central American and Caribbean countries.

tests for linkages among markets in terms of the second moments of the exchange rates. This approach refers to the idea that volatility movements across currencies are driven by common factors (e.g., oil prices, policy coordination). If common volatility exists, the manner in which the currencies evolve is closely related.

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. Furthermore, identifying a common volatility process is of interest because in the past few years there has been an effort to consolidate and increase the markets for derivative trading in Latin America. There are already several securities exchanges in the region that trade derivative contracts and over-the-counter derivative markets are emerging domestically. Any risk reduction through the identification of intracurrency relationships would be beneficial. Thus, the finding that these currencies have a common volatility process or that they are cointegrated could be useful information for the creation of cross-hedging policies based on derivatives (e.g., FX swaps).[4] Finally, it could indicate the likelihood of "contagion" in these markets.

Studying volatility dynamics among Latin American countries is important because volatility can impose economic costs on agents in the market. We focus on conditional volatility because it deals with the uncertainty about the exchange rate. Though the empirical evidence is mixed, it is known that economic agents bear higher transactions costs given the possibilities of unanticipated movements in the exchange rates.

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. The gist of the methodology is that a feature is shared by two series if they exhibit the feature individually, and if there is a linear combination of the two series that does not exhibit the feature.

[4] The market for derivatives in Latin America is emerging. 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 (The 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.

Given that the feature of interest is the existence of common ARCH, we first test each currency for time-dependent variance. Then we form bivariate portfolios and test them for common volatility. Under the null hypothesis of common volatility, making use of a generalized method of moment (GMM) type of estimation, we look for a parameter λ that minimizes the Lagrange multiplier (LM) statistic for each of the portfolios. To the best of our knowledge, only three papers have tested for a common volatility process among exchange rates (Alexander 1995a; Funke and Hall 1995; and Farrell 2001), and none have used data for Latin America.

The paper is organized as follows. Following this introduction, Section 2 discusses the relevant literature on common features. Section 3 discusses the theoretical background and econometric methodology. In Section 4 we describe the data and the stochastic properties of the exchange rates in Latin America. In Sections 5 and 6, we use daily and weekly data for the 1994–2005 period to test for cointegration and for common volatility in the foreign exchange market. We focus on this last decade as many countries in Latin America have moved towards a more flexible system of exchange rates. Section 7 presents a summary and concluding remarks.

2. Review of the Literature

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.

The most popular and widespread application of the common feature concept is the test for cointegration, developed by Granger (1983) and Engle and Granger (1987). Cointegration is a cofeature test for two or more series, which individually are not stationary but for which a linear combination of the series is stationary. Following the developments in cointegration, interesting applications of the common feature methodology of Engle and Kozicki (1993) have been undertaken. For example, in the area of business cycles, the test has been used to identify common cycles, cycle codependence, common autocorrelation, and the degree of business cycle integration. The test has also been applied to identify the common presence of other features such as seasonal components, non-linearities, serial correlation, structural breaks, kurtosis, skewness, and seasonality.[5]

Another interesting feature that time series usually display is time-varying variance. Hence, the common feature methodology has also been extended to test for the presence of common ARCH. The common ARCH test is based on factor-ARCH structure models such as those proposed by Engle (1987) and Diebold and Nerlove (1989). In these factor models, asset prices are driven by factors (a small number of latent variables) and by idiosyncratic disturbances. In the common volatility application, the factor model specifies a covariance matrix having the property of a linear combination with "no ARCH."

In international finance, this methodology has been used to analyze the existence of common volatility in stock and bond markets and in the interest rate term structure for a number of countries (see Alexander 1995b; Arshanapalli and Doukas 1994; Arshanapalli et al. 1997; Booth et al. 1996; Booth and Tse 1996; Engle and Marcucci 2005; Engle and Susmel 1993; Tse et al. 1996; and So et al. 1997).

This paper investigates the linkages and the volatility process across Latin American currencies by testing for first- and second-order common features. These common features generally arise when the series exhibit comovements, i.e., when they are generated by common factors. Evidence of common features in the foreign exchange markets has substantial implications. From a macroeconomic perspective, it is an indicator of a movement towards financial integration. From the point of view of investors, it has implications in terms of the assessment of risk and the development of derivative trading strategies.

The two types of features sought in this paper are common stochastic trends and common ARCH factor. We employ cointegration analysis to test for common stochastic

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[5] For a more complete literature review on different applications of the testing procedure, see two special editions covering theoretical and empirical advances on common features: Journal of Business and Economics Statistics, 11 (1993) and Journal of Econometrics, Forthcoming (2005).

trends. The existence of common volatility (common ARCH) is achieved by using a factor ARCH model and the Engle and Kozicki (1993) methodology. The empirical application of cointegration in foreign exchange markets has been widespread. However, the common volatility approach to the exchange rates has been limited.

The literature on the existence of common stochastic trends among nominal exchange rates has focused mainly on the case of major world currencies. For the most part there have been two interpretations about the existence of cointegration among a system of exchange rates. On the one hand, it has been interpreted to have implications for the market efficiency debate. If markets are efficient, there should be no cointegration among currencies. Any evidence of cointegration implies Granger causality running in at least one direction; thus, economic agents can make use of such information to make riskless profits, violating the principle of efficient markets (see Aroskar et al. 2004; Diebold et al. 1994; Hakkio and Rush 1989, 1991; and McDonald and Taylor 1989).

The other interpretation of cointegration is in regard to financial convergence and international policy coordination. Financial convergence results in a path of long-run equilibrium among economic variables such as the exchange rates (Aggarwal and Mougoue 1998; Jeon and Lee 2002; Lee 2003). Hence, a finding of cointegration would imply financial convergence.

In general, the empirical evidence on cointegration in exchange rates is mixed. It has been argued that this mixed evidence is due mainly to the statistical properties of the tests used. Most cointegration tests assume that all the elements of a vector are I(1) processes, while the cointegrating equation is presumed to be I(0). It has been claimed that exchange rates might not be cointegrated but instead may have a long memory-generating process, thus being fractionally cointegrated. In this case, the error correction term need not to be consistent with an I(0) process because it responds more slowly to shocks. Thus, deviations from the equilibrium are more persistent.

We use Johansen's (1991, 1995) cointegration test. Therefore, we concentrate on the finding that cointegration among exchange rates implies I(0) cointegrating equations. Not finding evidence of cointegration among the series may imply that we are overlooking fractional cointegration, the possibility that there is a long-run equilibrium relationship between the series, but deviations persist for a longer period.

The literature on common volatility to date and the use of high frequency data for emerging countries has been limited. To our knowledge, only three papers use the common feature methodology to uncover common volatility in the foreign exchange markets: Alexander (1995a), Funke and Hall (1995) and Farrel (2001).

Alexander (1995a) uses daily and weekly data on nominal U.S. dollar and German mark returns (with respect to several major currencies) to test for common ARCH factors. Her findings indicate strong evidence of a common ARCH factor only in the British sterling/U.S. dollar and Japanese yen/U.S. dollar weekly returns. No common ARCH is found in any of the German mark returns. The volatility comovements among the yen and the sterling were found to be in opposite directions. Furthermore, there is evidence that the volatility dynamics in the sterling and yen are important determinants of future volatility in other currencies.

Funke and Hall (1995) test for common features in the sterling/deutschmark, the sterling/dollar and the deutschmark/dollar exchange rates. They find strong evidence that a common underlying process drives the volatility of the sterling/U.S. dollar and the deutsche mark/ U.S. dollar. In contrast, they find that the cross rate between the sterling and the deutsche mark has nothing in common with the bilateral rates with respect to the dollar. They argue that in foreign exchange markets, convergence in second moments may take place more rapidly than convergence in first moments, and that the underlying shocks affecting the European currency markets have more in common than one might suppose by looking at movements in the level of exchange rates.

Finally, Farrell (2001) tests for a common volatility process in South Africa's dual exchange rate system and for the presence of volatility spillovers. His findings indicate no evidence of common volatility in the dual foreign exchange market of South Africa.

3. Theory and Econometric Methodology

The theoretical developments on cointegration have been widely applied in the literature. In contrast, the concept of common volatility is less known and its applications less common. Some of the most important applications of the common feature methodology in foreign exchange markets are the analysis of volatility comovements and the study of the possibilities of cross hedging. In the first case, we can identify the direction of volatility comovements when responding to a common factor. In the second case, the analysis can highlight how 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. Additionally, the amount and types of existing common features are indicators of the degree of market integration.

The common volatility approach to the common feature testing is based on factor models. In this type of model, asset prices are driven by a small number of latent variables, called factors, and by idiosyncratic disturbances. The importance of these models is that the number of latent variables is small; 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 2005). Following the application of Engle and Susmel (1993) to stock markets, we can also construct a simple factor model for currency returns. Suppose that returns on assets denominated on two Latin American currencies, denoted by x_{1t} and $x_{2t,}$ are generated as follows:

$$\begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix}_{(2x1)} = \begin{bmatrix} p_{1t} \\ p_{2t} \end{bmatrix}_{(2x1)} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}_{(2x1)}$$

Or, in a more compact fashion:

$$x_t = p_t + \varepsilon_t \tag{3.1}$$

where

$$\begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}_{(2x1)} = \begin{bmatrix} \gamma_{1t} \\ \gamma_{2t} \end{bmatrix}_{(2x1)} f_t + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}_{(2x1)}$$

or again, in a more compact fashion:

$$\varepsilon_t = \Gamma f_t + u_t \tag{3.2}$$

Here, x_t is a vector of observed currency returns, and p_t is the vector of time varying risk premia on the portfolio. The vector of unexpected components of the returns (ε_t) has two parts, an idiosyncratic country risk component (u_t) and a common factor component (Γf_t). We assume one common factor f_t. The factor loadings are specified by Γ (the sign and size of the effect that the factor has on the currency return). The expectation of the common future factor and idiosyncratic country risk is zero. That is:

$$E_{t-1}(f_t) = E_{t-1}(u_t) = 0 \tag{3.3}$$

and

$$E_{t-1}(f_t u'_t) = 0\,,\ E_{t-1}(f_t^2) = \sigma_t^2 \tag{3.4}$$

$$E_{t-1}(u_t u_t') = \Omega_t$$

Where, as in Diebold and Nerlove (1989), we impose the restriction that the variance of the idiosyncratic factor is held constant over time ($\Omega_t = \Omega$). Now, if $p_t = 0$, the conditional variance of the portfolio returns can be expressed as:

$$V_{t-1}(x_t) = V_{t-1}(p_t + \varepsilon_t) = V_{t-1}(\varepsilon_t)$$

$$= V_{t-1}(\Gamma f_t + u_t) = V_{t-1}(\Gamma f_t) + V(u_t)$$

$$= \Gamma\Gamma'\sigma_t^2 + \Omega \tag{3.5}$$

This model, based on arbitrage pricing theory (APT), assumes that the factor follows an ARCH process. 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. That is, a linear combination of the two series does not display conditional heteroscedasticity. Now, suppose that x_{1t} and x_{2t} have the following properties:

$$x_{1t} = f_{1t} + \eta_{1t} \quad \text{where } f_{1t} / I_t \sim d(0, h_t^2) \tag{3.6}$$

and

$$x_{2t} = f_{2t} + \eta_{2t} \quad \text{where } f_{2t} / I_t \sim d(0, k_t^2) \tag{3.7}$$

Where I_t denotes the information available 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:

$$V_t(y_t(\lambda)) = h_t^2 + \lambda^2 k_t^2 + 2\lambda Cov_t(f_{1t}, f_{2t}) + (\sigma_1^2 + \lambda^2 \sigma_2^2) \tag{3.8}$$

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 his investment if both currencies share a common volatility process. In this case, he reduces the risk of the portfolio to $V_t(y_t(\lambda)) = (\sigma_1^2 + \lambda^2 \sigma_2^2)$. Thus x_{1t} and x_{2t} could be combined in proportion $(1, \lambda)$ for effective hedging of volatility. The scale factor λ would be interpreted as the relative weight in a risk-minimizing portfolio. 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 simultaneously to 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 1995a).[6]

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 four steps. The first step is to test for univariate ARCH factors in each currency return. This paper uses squared currency return as a proxy of the realized volatility (x_t^2).[7] We estimate Engle's (1982) Lagrange multiplier (LM) test, which is distributed as χ^2 with degrees of freedom equal to the number of overidentifying 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 and Central America (MARCH-NC), and the other contains lags of South American countries (MARCH-SA).[8] The idea of this second test is to identify whether other currencies in the region are able to explain the volatility process in each country.

From steps one and two, 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"

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[6] The case where multiple λ's are found is possible. In this case, it would suggest than more than one combination of the currencies will result in a constant variance portfolio. In this case, the sign can be weighted according to the average or number of times each sign appears.

[7] This section focuses on the volatility process of the exchange rates and therefore does not model the mean of the process. Rather, the section uses 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).

[8] 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.

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 misleading results. This combination might yield a critical value that implies a failure to reject the null hypothesis and incorrectly conclude that both series have common volatility. This situation also holds for the case in which both series, individually, do not have ARCH.[9]

In the third step, 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.[10] 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 generalized method of moments (GMM) (Hansen 1982) type of estimation, which follows a χ^2 distribution with degrees of freedom equal to the number of overidentifying restrictions.

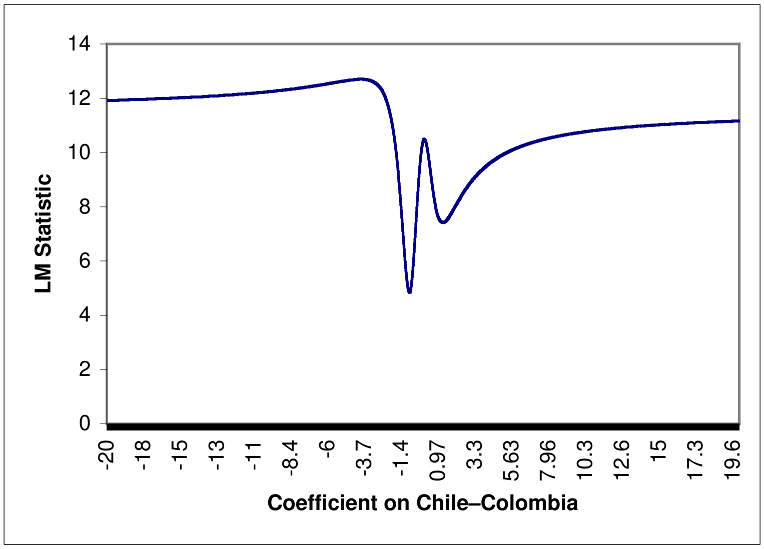
The minimization is conducted through a quasi-Newton optimization method, BFGS, and through a grid search with inclusive bounds of –100 and 100 and in a 0.01 sequence.[11] We expanded the interval for the grid search whenever the minimization resulted in λ equaling one of the bounds. In Figure 1 we show the case of a bivariate portfolio consisting of the Chilean peso and Colombian peso, where Chile's coefficient was normalized to be one.

[9] 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.

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

[11] BFGS stands for Broyden–Fletcher–Goldfarb–Shanno. Both methods were used as means of robustness. The results did not differ much and both led to similar conclusions. The grid search helped us to identify if the minimum was well defined. In fact, when looking at all combination of currencies, we find that, in general, although the shapes of the functions are not globally convex, the minimum is well defined, as previously demonstrated by Engle and Kozicki (1993).

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



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. However, for robustness, a fourth step is required. In this last step the portfolios that share common volatility need to pass new univariate and multivariate ARCH tests. These new tests consist of regressing the optimal portfolios (given λ) on their own lags and on lags of other countries. Remaining ARCH in the portfolios can be an indication of no common volatility.

4. Data Description

In this paper, we use data for fourteen Latin-American currencies. The sample period begins with January 3, 1994, and ends with February 8, 2005, for a total of 2,896 daily and 577 weekly observations. The data corresponds to the closing bid and is obtained from Bloomberg's database and from some of the countries' central banks. The sample contains the currencies of Argentina (AR), Bolivia (BO), Brazil (BR), Colombia (CO), Chile (CH), Costa Rica (CR), Guatemala (GU), Mexico (ME), Nicaragua (NI), Paraguay (PA), Peru (PE), Dominican Republic (RD), Uruguay (UR) and, Venezuela (VE), all vis-à-vis the U.S. dollar.[12] (The appendix contains detailed explanation of the data and sources).

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.[13] 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 estimations. 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 this last decade because, during this period, the currencies of the sample have gradually moved towards more flexible exchange rate systems. Whenever the exchange rate in levels is analyzed, we use the logarithm of the nominal exchange rate. The first differences of the logarithm of the nominal exchange rates are used to analyze currency returns.[14]

4.1. Univariate Descriptive Statistics

Daily and weekly univariate statistics for the currency returns are provided in Table 1. When examining both daily and weekly data, the highest values, in terms of standard deviations, are those of Argentina, Brazil, Mexico, Dominican Republic, and Venezuela. In general, all the series appear to be better characterized as leptokurtic or "fat tailed," which is a common characteristic found in speculative prices and financial returns. The presence of fat tails indicates that the series possibly either have infinite variances or volatility clustering. Therefore, volatility measures might be inadequately specified using the

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[12] The data on exchange rates, used in this paper, pertains to the official market. For some currencies, there might be significant foreign exchange traded in parallel or black markets, which coexist with the official market.

[13] Baillie and Bollerslev (1989) find that, for six major currencies, Monday prices still reflected the accumulation of news that occurred since the market closed on Friday.

[14] We use nominal exchange rates rather than real exchange rates given that we are using daily and weekly data for which data in real exchange rates are not available. Also, using real exchange rates would have different implications for the conclusions derived from the tests. The log of the nominal exchange rates is expressed in foreign currency received for one U.S. dollar. 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.

estimated variance, thus the importance of conditional measures of risk and volatility such as those provided by ARCH and GARCH estimates (Fofack and Nolan 2001; Pozo and Amuedo-Dorantes 2003).

The most notable cases of leptokurtosis were those of Argentina, Bolivia, Mexico, Paraguay, and Venezuela given the high values for kurtosis observed. Only Nicaragua and Costa Rica are platykurtic. The Ljung-Box (LB) statistic is an autocorrelation test that follows a χ^2 distribution with q degrees of freedom. The LB statistic suggests significant autocorrelation, which in turn also suggests evidence for a time varying variance.

The skewness parameter of the distribution of exchange rates is of importance because it can capture the presence of a small number of large movements in any direction. If there is a case in which the exchange rates were subject to a single unusually large depreciation during a particular period, this would appear in the skewness of the distribution during that period. A positive value of skewness indicates the presence of a few relatively large devaluations during the period while a negative value indicates a few large appreciations.

The fact that most currencies in our sample have a positive skewness reflects the tendency in these countries towards policies oriented to devaluate. Argentina, Mexico, Nicaragua, Paraguay, and Venezuela display the most pronounced assymmetries. Paraguay is highly skewed to the left, while the Argentinean and Venezuelan currencies have high positive skewness coefficient. 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.

In accordance with the literature on exchange rates, Latin American currency returns are characterized by asymmetric non-normal unconditional distributions, and they exhibit higher probability in the tails relative to the normal distribution. Furthermore, the effect of increasing the length of the sampling interval results in a reduction in kurtosis (see Boothe and Glassman 1987; Baillie and Bollerslev 1989).[15]

4.2. Stationarity Properties

To distinguish the appropriate order of integration of the series, we check for the presence of unit roots. We conduct a battery of tests on the log of exchange rates: the augmented Dickey–Fuller (ADF) and the Kwiatkowski et al. (1992) (KPSS) tests. The ADF test is a test under the null hypothesis that the series follows a unit root process against the one-sided alternative of stationarity. For the KPSS test the series is assumed to be trend-stationary under the null hypothesis.[16]

Results for daily and weekly observations are presented in Table 2. As frequently found for nominal exchange rates, using the ADF test, we fail to reject the null hypothesis of a random walk for most of the exchange rates in our sample. We also reject the null hypothesis of stationarity for all currencies using the KPSS test. Most currencies in our sample are stationary in first differences (I[1]), only two are found to be I(2).

If we do not allow a trend in the ADF specification, we reject the null hypothesis of a unit root for the Brazilian real and the Mexican peso. However, both are difference-stationary for the ADF trend specification. Also, the examination of the time plots of all currencies indicates that they are clearly nonstationary in levels, and this result is corroborated by the KPSS test. The KPSS test is able to identify that all series are not stationary in levels, while the null of stationarity is not rejected for the logarithmic difference of exchange rates. The Costa Rican and Nicaraguan currencies have two unit roots and therefore are excluded from subsequent analysis. In conclusion, with the exception of these last two, all currencies in our samples have one unit root.

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[15] We also performed an analysis with fortnightly and monthly data and concluded in favor of this observation. These results are not included in this paper but are available from the author upon request.

[16] The augmented Dickey–Fuller (ADF) test is a test under the null hypothesis that the series follows a unit root process against the one-sided alternative of stationarity. The appropriate number of lags is determined by the Schwartz information criteria (SIC) $-2(l/T) + 2k\log(T)/T$. We use MacKinnon (1991) lower-tail critical and p-values for this test. The KPSS test differs from the ADF test in that the series is assumed to be trend-stationary under the null. The reported critical values for this LM test statistic are based upon the asymptotic results presented in Kwiatkowski, et al. (1992, Table 1, p. 166).

5. Cointegration Analysis: Are There Common Stochastic Trends?

Economics integration among Latin American countries has been increasing during recent years with respect to the level of trade among the countries, an outgrowth of the successful negotiation of a number of subregional trade agreements (e.g. LAIA, Mercosur, Group of Three (G3), and more recently, CAFTA.) Increased trade integration may have increased the transmission of currency movements and shocks across countries. Moreover, several currency and financial crises have taken place (Mexico 1994, Brazil 1999, and Argentina 2000s). These crises have prompted economists to question whether extreme currency movements are more likely to result in contagion across regions. As a result, it is important to understand the stochastic properties and the relationships among Latin American currencies. These issues are important for cross-border investors, multinational firms, central banks, and foreign exchange market participants.

In this section we test for cointegration among exchange rates in Latin America. Finding evidence of cointegration means that some common driving fundamentals determine the long-run movements in the group of exchange rates. Knowing that there is cointegration among exchange rates points to financial integration in the region. It also implies that cross-hedging policies based on derivatives can be developed. On the other hand, rejecting cointegration means that the currencies respond to their own particular set of fundamentals or forcing variables (Baillie and Bollerslev 1989).

We test for cointegration in multivariate systems of Latin American currencies using the Johansen (1991, 1995) methodology. In general, we test the null hypothesis of whether a system of exchange rates contains from $r = 0$ up to $r = k\text{-}1$ number of stochastic trends, where k is the number of currencies in the system. For the interpretation of the empirical results, we claim "complete" convergence among a set of k countries if we find $k\text{-}1$ cointegrating vectors. Otherwise, if r is found to be in the interval $0<r<k\text{-}1$, we say that only "partial" convergence has been achieved.[17]

We fit VAR systems of the currencies in levels to first specify the lag length to be considered in the cointegration test. Provided that the specifications had white noise

[17] See Enders (2004, Chapter 6) for more details in this regard.

residuals, the lag length was chosen by minimizing the Schwartz information criteria (SIC). We examine a system for all the currencies and then we divide the sample of currencies into two subsamples (similar approaches have been undertaken by Aroskar et al. 2004, and Jeon and Lee 2002). The first subsample is for the period 1994–2000. During this period there were several financial crises and most currencies underwent speculative attacks. The second subsample is for the 2001–2005 period. Although there still was some foreign exchange pressure and financial instability in a few countries, during the latter period there appeared to be fewer shocks and most countries had already declared flexible exchange rate systems.[18]

We test for a cointegrating relationship based on Johansen's maximum eigenvalue and trace statistics.[19] We carry out our testing analysis, allowing for both an intercept and an intercept and trend in the cointegrating equation. Table 3 displays the information on the cointegration tests for the region during the whole period and for the two subperiods. These two periods are separated to investigate whether the different financial crisis in the region affected foreign exchange market cointegration patterns. At the 5% level of significance, the results for daily data indicate that for eleven countries (Costa Rica and Nicaragua are excluded in all tests as they did not have the same order of integration), there is evidence of partial cointegration. Results hold for the crisis and non-crisis periods. However, notice that there is a reduction in the number of cointegrating equations during the 1994–2000 period.

We also conducted a series of bivariate cointegration tests (Table 4). The results indicate that for the whole period, most currencies are cointegrated with Brazil. This relationship holds for the 1994–2000 period. However, after the year 2001 these cointegration relationships with Brazil disappear. On the other hand, Uruguay is

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[18] These two periods were chosen ad hoc on the basis that the crisis periods in most countries happened before the year 2001. Argentina is omitted from the 1994–2000 period since the Argentinean peso was pegged to the U.S. dollar for most of this period.

[19] The trace statistic tests the null hypothesis of r cointegrating relations against the alternative of k cointegrating relations, where k is the number of endogenous variables, for r = 0,1, ...k-1. The trace statistic for the null hypothesis of r cointegrating relations is computed as: $LR_{it}(T/k) = -T\sum_{i=r+1}^{k}\log(1-\lambda_i)$ where λ is the i-th largest eigenvalue. The maximum eigenvalue statistics is $LR_{\max}(r/r+1) = -T\log(1-\lambda_{r+1})$.

cointegrated with most currencies during the 1994–2000 period and after that period such relationships are only maintained with Argentina, Bolivia, and Colombia.

We performed cointegration analysis for weekly data and find evidence of partial cointegration for the system of eleven countries as indicated by both the maximum eigenvalue and trace statistics (Table 5). Due to the limited number of observations in weekly data, we do not discriminate among different periods. Bivariate cointegration tests (Table 6) reveal, once again, that the Brazilian real is cointegrated with most of the currencies in our sample.

In order to address the issue of regional integration with more detail, in Tables 7 and 8 we report the results for daily and weekly data for the currencies in the region according to economic group or trade areas (i.e., Mercosur, G3, CAFTA, and LAIA).[20] From the results we find that there is evidence of partial cointegration for the Mercosur area. When we include both Chile and Bolivia (which later joined the Mercosur area), the result of partial cointegration continues to hold. Similar results were obtained for the LAIA region, the Andean community and the countries from the CAFTA. However, for the G3 (Venezuela, Colombia, and Mexico), both test statistics indicated no cointegration. These results hold even when we analyze weekly data.

In general, from these results, there is evidence of partial cointegration among Latin American currencies, and a noticeable pattern of cointegration is found for some of the subregional trade areas. The analysis of subperiods indicates that during the 1994–2000 period, Latin American currencies are cointegrated and most of them with respect to the Brazilian real. Thus, we find the Brazilian real to be the one currency leading the long-run equilibrium in Latin America in the 1990s. However, after the year 2000 these relationships disappear.

These results are indicative of two things. First, cointegration patterns in the region and among trade areas support the idea that Latin American countries displayed some degree of nominal convergence in their foreign exchange markets. However, after the year 2000, there is no evidence of cointegration. A possible explanation lies in the fact that after

[20] The data appendix contains a detailed summary of the trade areas along with their respective memberships.

the year 2000, many of these countries opted for less central bank intervention in terms of foreign exchange and it might be that markets are becoming more efficient.

6. Common Volatility in the Foreign Exchange Market

In this section we apply the common features methodology developed by Engle and Kozicki (1993) to test for the existence of common volatility in Latin American foreign exchange markets. The idea of the common-feature methodology is that if we have two series and each displays time-varying volatility, we can find a linear combination of the two series that does not display time-varying volatility. In this case, by finding such a combination we are offsetting any ARCH factor and reducing the portfolio's risk. Furthermore, say we find a factor λ that gives us a "no ARCH" portfolio. A negative λ means that the volatility processes go in the same direction and that time-dependant volatility is offset with a combination at a proportion (1, λ). Hence, two conclusions are derived: first, a factor λ that provides suggestions for risk reduction in portfolio formation, and second, the response and direction of the volatility process in the two countries' currencies when affected by common shocks.

6.1 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." To conduct the LM test, each return series is squared and used as an approximation for each country realized volatility. The squared returns are regressed against a constant and lags of itself. We use 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 9. The 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 results for Argentina are the lowest when compared with the other countries. 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 two sets of information: one for the Central and North American countries (MARCH-NCA) and another for South American countries (MARCH-SA). The goal is to find out if introducing other currencies as explanatory variables can capture ARCH. [21]

Results are reported on the last four panels of Table 9. *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, while the South American countries are good at detecting ARCH, North and Central American countries are not good to capture ARCH effects. 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.[22]

The test for common volatility is conducted for all possible bivariate portfolios. Venezuela is excluded from the analysis because of its absence of time-varying variance. In the absence of ARCH, there cannot be common ARCH. Not a single common ARCH is found when testing common volatility for the whole period (1994–2005). Next, in order to investigate the possible effects of including and excluding crisis periods, we divide the sample into two subperiods (1994–2001 and 2001–2005).[23] We do not find evidence of common volatility during the earlier period. However, in the second subsample (2000–2005), we were able to find portfolios possibly sharing common volatility. Table 10 shows

[21] 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.

[22] We also conducted bivariate ARCH tests, but the results are not presented due to space constraints. The results are in line with the conclusions obtained from the MARCH test. Results are available from the author upon request.

[23] All currencies except Venezuela displayed time-varying variance for both periods. Argentina is not included in the analysis for the 1994–2000 period because it was pegged to the U.S. dollar for most of this period.

the results of testing for "common volatility" in daily data for the 2000–2005 period where the TR^2 is minimized over λ. Most pairs of countries possibly sharing common volatility were in relation to the Mercosur countries and Colombia.

As mentioned previously in the paper, as means of robustness and to ensure that these "no ARCH" portfolios indeed share a common conditional time-dependent volatility process, we subject them to a new univariate and multivariate ARCH tests. These new tests are as follows: first, for the univariate test we conduct a regression of the optimal portfolio (given by λ) on a constant and its own lags; then, in addition to the own lags, we include lags of other countries' squared currency returns. If the portfolio passes these new univariate and multivariate ARCH tests and no further evidence of ARCH is evident, we can safely deduce that a "no-ARCH" portfolio exists and that the two countries share a common volatility process (with scale factor λ) in their foreign exchange markets.

The last two columns in Table 10 display the results on these two new tests. Both tests indicate that there is still time-varying variance for all of the portfolios. Therefore, for daily data, there is lack of evidence of a common volatility process in terms of the foreign exchange markets.[24]

6.2. Weekly Returns

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, the null hypothesis of "no ARCH" is rejected for most of the currency returns at the 5% level of confidence (see Table 11). Thus, most currencies pass the first test and are included in the test for common volatility. The last four panels present the estimates of the multivariate test. The Venezuelan Bolivar did not pass any of the tests. As a result, this currency is not included in the tests for common volatility.

A graphical analysis is presented in Figure 2. Figure 2 reports the annualized volatility plots for all currency returns. These are obtained from the GARCH (1,1) estimations

[24] A common explanation for the lack of common ARCH in daily data is that daily data might be too noisy to detect any common feature (see Engle and Susmel 1993; Alexander 1995).

reported in Table 12. The reported quasi-maximum likelihood estimates of univariate generalized autoregressive conditional heteroscedastic GARCH models are of the form $x_{it} = f(x_t; ß) + u_t$, where, $u_t/\psi_{t-1} \sim \mathbf{D}(0, h_t^2)$.[25]

Table 13 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, Chile, Colombia, and Guatemala. We subject each of these portfolios to another univariate and multivariate ARCH test to confirm that they indeed share a common conditional time-dependent volatility process. The last two panels in Table 13 display the results on these two new tests.

Both tests indicate that most portfolios still display time-varying variance; therefore, these portfolios do not share a common volatility process. However, three markets seem to be related through their second moments: Argentina–Uruguay, Chile–Colombia, and Colombia–Guatemala. The portfolio including Argentina and Uruguay displayed common conditional variance with a factor $\lambda = 0.84$. This suggests that the movements on the conditional volatility of Argentina are larger than in the conditional volatility of the Uruguayan currency returns.

The λ coefficient for Colombia and Guatemala was 0.34, also indicating that the movements of the conditional volatility of Colombia are larger than those of Guatemala. Furthermore, the common conditional volatility of these two pairs of countries moves in opposite directions. On the other hand, Chile and Colombia have a common ARCH factor that moves in a similar direction, which weakens and strengthens in the same fashion.

7. Summary and Concluding Remarks

Recent movements towards economic and policy convergence among Latin American countries and the interdependency created due to the efforts in achieving trade and financial integration are the main motivation for this paper. Such a situation invites us

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[25] We specify the mean equation as either an AR (1) process or having a constant mean. We want to concentrate mainly on the variance process. The error term (u_t) follows, conditional on ψ_{t-1}, a **D** distribution and the conditional errors have zero mean and time-varying variance, h_t^2. The distribution (**D**) is set to be normal. The quasi-maximum likelihood estimation is performed with robust standard errors computed using the method of Bollerslev and Wooldridge (1992).

to question and inquire about the role of exchange rates. Very little is known about the characteristics of high frequency exchange rate data in Latin America. Thus, this paper contributes to the knowledge about Latin American nominal exchange rates by studying their stochastic properties. It also relates to the literature on financial markets' linkages by analyzing their cross-country interactions. To be specific, we test for first- and second-order common features (common stochastic trends and common volatility) in the foreign exchange markets.

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 the stochastic properties of Latin American exchange rates. Several characteristics and stochastic 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. The presence of leptokurtosis is an important feature to recognize when assessing different measures of volatility. Moreover, an important regularity is that most exchange rates have unit roots and thus are stationary in first differences. Only three currencies did not fit any of the stylized facts for exchange rates: the Venezuelan Bolivar, the Nicaraguan lempira, and the Costa Rican Colon.

The analysis of cointegration was carried out using Johansen's (1991, 1995) methodology. We tested cointegration based on the trace and maximum eigenvalue statistics. There was evidence of partial cointegration for Latin American currencies for both daily and weekly data. Furthermore, bivariate cointegration tests were conducted and revealed that the Brazilian real might have been the one currency driving the long-run equilibrium among Latin American currencies. However, when splitting the samples to separate the possible effects of currency and financial crisis that overcame the region, we found that cointegration of most countries with Brazil was present during the first subperiod (1994–2000) but this was not the case for the second subperiod (2001–2005).

The finding that most of the currencies are cointegrated with the Brazilian real implies that it might have useful information about the long-run path of other currencies in the region. Brazil is not only the largest economy in Latin America; it also has, as of 2004, one of the largest derivate markets in the world. Many investors follow the market performance of the Brazilian economy as an indicator of the performance of other economies in the region. A practice known as "putting all the other countries in the same bag." On the other hand, the finding that this relationship changes after the year 2000 might be an indication that, because currency markets are becoming more liberalized, either they are becoming more efficient or the currencies are responding to their own set of fundamentals.

Cointegration was also tested using different subsamples organized by the existing trade areas (i.e., Mercosur, G3, Andean Community, LAIA, CAFTA). Evidence of cointegration was found for both Mercosur and LAIA groups. On the other hand, nor or partial evidence of cointegration, was found for the G3 and Andean community. These results are in line with those of Escaith et al. (2002). Using trade variables, GDP, and financial variables, other than nominal exchange rates, Escaith et al. (2002) finds that economic and financial integration among countries in Latin America is more evident at the subregional level, particularly in the Mercosur.

Finally, in order to understand any common volatility process in the foreign exchange market, we made use of a factor ARCH model to test for common volatility. The test for common volatility was carried out using an application of Engle and Kozicki's (1993) common features methodology. First, we tested each currency for time-dependent variance. Then we formed bivariate portfolios and tested them for a common volatility process. We found that most of the currencies (with the exception of Venezuela) displayed time-varying variance.

In general, most countries appeared to have a stronger interaction in terms of volatility after the year 2001. However, robustness checks did not allow us to conclude in favor of common volatility for daily observations. From the results of the common volatility test in weekly data, we found that with a few exceptions, exchange rates in the region do not share a common volatility process. Thus, most countries' currency time-varying variance has not been driven contemporaneously by factors common to other currencies' volatility. In particular, only a common volatility process was found at the weekly frequency for Argentina–Uruguay, Chile–Colombia, and Colombia–Guatemala.

For financial variables, these results are not far from what has been found in the literature. For example, in the case of interest rates, Edwards and Susmel (2003) find that, during the 1990s, there is weak evidence of volatility comovements in interest rates across Latin American countries, and they do not support the existence of contagion. On the other hand, Berg et al. (2002) finds that the degree of comovements of several financial variables, including the exchange rates, is not higher among Latin American countries than it is among emerging markets more generally.

Our findings have several implications. We tried to uncover common factors affecting the volatility behavior but the variances seemed to be mostly country specific. We could not uncover region specific sources of variations. Therefore, intracurrency diversification within the region is not a straightforward strategy for portfolio risk reductions, and further analysis regarding properties of exchange rates in the area must be carried out. On the other hand, this weak evidence of common volatility could be due to different things: first, the different types of existing capital controls with countries exhibiting insulation from regional factors, and second, the fact that these countries have significant foreign exchange traded in the black markets, and common volatility might more likely be observed there rather than in the official markets.

Moreover, the level of unofficial dollarization in some of these countries is relatively high. Foreign currency–denominated bank deposits are large, particularly in Bolivia, Peru, and, Uruguay (92.5, 78.2, and 84.2 percentage share, respectively, of total deposits in the year 2000, Berg et al. 2002). Also, most countries with binding restrictions on onshore dollar deposits have a high degree of offshore deposits as a share for total deposits (such is the case of Brazil, Colombia, and Venezuela). Informal dollarization might prevent us from observing common volatility in the official markets.

A last implication of our findings is related to the model. It might be that, in fact, the idiosyncratic volatility component of each country's currency is time varying, thus violating the assumptions of the model. Common ARCH factors may exist, but individual ARCH factors may also exist dominating the volatility plot. Likewise, currencies might indeed respond to common volatility factors but with different lag responses (different timing), and this is not captured in the Engle and Kozicki (1993) test.[26]

8. References

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[26] Ericcson (1993) pointed out two methodological problems with the "common feature." The first concerns the dating of the series. The observed presence of a common feature is sensitive to the relative lag between the variables involved. Thus, if the relative lag is not correctly specified, the test might reject the existence of a cofeature even if it exists. The second limitation concerns the restrictive hypothesis about cofeatures due to their bivariate nature. Placing the common ARCH hypothesis in a bivariate context may be too restrictive.

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9. Data Appendix

All data series came from *Bloomberg's Database* except the Bolivian bolivariano, the Costa Rican colon, the Nicaraguan Cordoba, and the Dominican Republic peso, which come from their own Central Banks. Daily data corresponds to five days a week (weekends are excluded.) Missing observations due to holidays were replaced with the observation of the previous day. In total, about 46 replacements were made for most countries.

The names of the currencies that we use in this study are: Argentinean peso, Bolivian Bolivariano, Brazilian real, Colombian peso, Chilean peso, Costa Rican Colon, Guatemalan quetzal, Mexican peso, Nicaraguan Cordoba, Paraguayan guarani, Peruvian new sol, Dominican Republic peso, Uruguayan peso, and the Venezuelan Bolivar.

The trade areas along with their respective membership is as follows: **Latin American Integration Association** (LAIA, 1980): Argentina, Bolivia, Brazil, Chile, Colombia, Cuba, Ecuador, Mexico, Paraguay, Peru, Uruguay, and Venezuela. **Mercosur** (1991): Argentina, Brazil, Paraguay and Uruguay. **Andean Group** (1993): Bolivia, Chile, Colombia, Peru and Venezuela. **Group of Three** (G3, 1994): Mexico, Colombia and Venezuela. **Central American Free Trade Agreement** (CAFTA, 2005): Costa Rica, the Dominican Republic, El Salvador, Guatemala, Honduras, Nicaragua, and the United States.

Table 1. Summary Statistics for Daily (d) and Weekly (w) % Change in the Log of Exchange Rates (1/4/1994 – 2/8/2005)

Country	*Mean*	*Std. Dev.*	*Skewness*	*Kurtosis*	*LB*	*LBS*	*JB*
Argentina (d)	0.037 [b]	1.054	14.63 [a]	444.16 [a]	115.71 [a]	44.20 [a]	0.000
Argentina (w)	0.002 [b]	0.024	10.364 [a]	154.58 [a]	57.22 [a]	27.41 [a]	0.000
Bolivia (d)	0.020 [b]	0.005	2.11 [a]	230.97 [a]	360.84 [a]	348.75 [a]	0.000
Bolivia (w)	0.001 [a]	0.006	0.561 [a]	200.59 [a]	152.57 [a]	142.97 [a]	0.000
Brazil (d)	0.107 [a]	0.977	0.31 [a]	24.1 [a]	383.12 [a]	1341.9 [a]	0.000
Brazil (w)	0.005 [a]	0.028	1.641 [a]	13.88 [a]	341.59 [a]	411.07 [a]	0.000
Chile (d)	0.011	0.470	0.03 [a]	7.22 [a]	31.78 [a]	374.95 [a]	0.000
Chile (w)	0.0005 [a]	0.010	-0.088	5.36 [a]	28.33 [a]	30.70 [a]	0.000
Colombia (d)	0.037 [a]	0.476	1.03 [a]	15.88 [a]	5.57	229.69 [a]	0.000
Colombia (w)	0.002 [a]	0.010	0.619 [a]	5.84 [a]	40.35 [a]	38.92 [a]	0.000
Costa Rica (d)	0.039 [a]	0.022	- 0.28 [a]	-0.202 [b]	836.28 [a]	424.14 [a]	0.000
Costa Rica (w)	0.002 [a]	0.0006	0.687 [a]	4.19 [a]	871.40 [a]	760.65 [a]	0.000
Guatemala (d)	0.010 [a]	0.205	0 .14 [a]	18.30 [a]	147.95 [a]	124.37 [a]	0.000
Guatemala (w)	0.0005 [a]	0.005	0.760 [a]	8.28 [a]	20.22 [a]	20.35 [a]	0.000
Mexico (d)	0.044 [b]	1.032	1.620 [a]	102.35 [a]	83.123 [a]	1172.9 [a]	0.000
Mexico (w)	0.002 [a]	0.019	4.603 [a]	43.62 [a]	46.21 [a]	124.56 [a]	0.000
Nicaragua (d)	0.033 [a]	0.023	1.782 [a]	5.32 [a]	2871.0 [a]	2945.9 [a]	0.000
Nicaragua (w)	0.002 [a]	0.0005	-0.074	- 1.92 [a]	3329 [a]	3337.4 [a]	0.000
Paraguay (d)	0.043 [a]	0.727	- 2.78 [a]	139.72 [a]	79.79 [a]	185.75 [a]	0.000
Paraguay (w)	0.002 [a]	0.012	0.825 [a]	13.73 [a]	24.15 [a]	190.77 [a]	0.000
Peru (d)	0.014 [a]	0.287	0.990 [a]	45.31 [a]	75.63 [a]	451.92 [a]	0.000
Peru (w)	0.0007 [a]	0.006	0.302 [a]	11.04 [a]	17.89 [a]	122.15 [a]	0.000
D. Republic (d)	0.023	1.028	0.590 [a]	49.68 [a]	106.5 [a]	839.66 [a]	0.000
D. Republic (w)	0.002	0.023	0.774 [a]	27.52 [a]	14.04 [b]	84.01 [a]	0.000
Uruguay (d)	0.059 [a]	0.010	0.830 [a]	77.36 [a]	252.04 [a]	1135.4 [a]	0.000
Uruguay (w)	0.003 [a]	0.016	0.085	27.38 [a]	44.88 [a]	652.2 [a]	0.000
Venezuela (d)	0.099 [a]	1.736	20.40 [a]	619.65 [a]	10.08	0.048 [a]	0.000
Venezuela (w)	0.005 [a]	0.038	8.883 [a]	113.04 [a]	5.44	0.059 [a]	0.000

Note: [a], [b] and [c] indicate significance at the 1%, 5% and 10% level. 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. Under the assumption of normality, their asymptotic distribution is s~N(0, 6/T) and k~N(0,24/T).

Table 2. Tests for Unit Root in the Daily (d) and Weekly (w) Log of Exchange Rates (1/4/1994 – 2/8/2005)

	ADF				*KPSS*
Country	*Trend*	*Lags*	*No Trend*	*Lags*	
Argentina (d)	-1.61	24	-0.38	24	4.48
Argentina (w)	-2.29	12	-1.04	12	2.07
Brazil (d)	-2.50	3	-4.06 [a]	17	6.01
Brazil (w)	-3.39 [b]	6	0.17	4	3.13
Bolivia (d)	-1.73	9	-0.01	9	6.80
Bolivia (w)	-1.41	4	-8.97 [a]	4	2.89
Chile (d)	-0.88	2	-0.76	2	6.16
Chile (w)	-0.93	2	-0.75	0	2.82
Colombia (d)	1.21	2	-1.56	2	6.70
Colombia (w)	0.56	2	-1.45	4	3.07
Costa Rica (d)	-0.43	22	-2.44	22	6.76
Costa Rica (w)	-2.46	14	-2.81 [b]	14	3.11
Guatemala (d)	-2.09	1	0.32	2	6.32
Guatemala (w)	-2.10	1	0.23	0	2.90
Mexico (d)	-2.96	27	-3.29 [b]	27	4.60
Mexico (w)	-2.75	1	-3.21 [b]	1	2.17
Nicaragua (d)	-1.80	25	-2.20	11	6.71
Nicaragua (w)	-1.91	2	-2.22	2	3.09
Paraguay (d)	-1.74	3	0.01	3	6.66
Paraguay (w)	-1.69	0	0.02	0	3.05
Peru (d)	1.04	3	-2.36	3	6.04
Peru (w)	0.77	0	-2.19	0	2.77
D. Republic (d)	-1.67	2	-0.51	2	4.85
D. Republic (w)	-1.53	0	-0.43	2	2.23
Uruguay (d)	-1.41	24	-1.47	24	6.33
Uruguay (w)	-1.87	7	-1.39	6	2.92
Venezuela (d)	-2.51	1	-1.68	0	6.15
Venezuela (w)	-2.50	0	-1.68	0	2.86

Note: [a], [b] and [c] indicate significance at the 1%, 5% and 10% level. The Augmented Dickey Fuller (ADF) test is a test under the null hypothesis that the series follows a unit root process against the one sided alternative of stationarity. The appropriate number of lags is determined by the Schwartz information criteria (SIC) -2(l/T) + 2klog(T)/T. We use MacKinnon (1991) lower tail critical and p-values for this test. The KPSS test differs from the ADF test in that the series is assumed to be trend-stationary under the null. The reported critical values for this LM test statistic are based upon the asymptotic results presented in KPSS (1992) (Table 1, p. 166).

Table 3. Daily Estimates: Unrestricted Cointegration Test

Period		*Trace*		λ_{max}	
	Ho: No. of CE	With Trend	Without Trend	With Trend	Without Trend
1994-2005	None	821.34 [a]	653.12 [a]	248.89	248.72 [a]
	At most 1	572.44 [a]	404.40 [a]	242.43	133.24 [a]
	At most 2	330 [a]	271.17 [a]	87.20	79.97 [a]
	At most 3	242.80 [a]	191.19	67.01	50.18
	At most 4	175.78	141.02	50.17	38.46
	At most 5	125.62	102.56	38.14	33.50
	At most 6	87.47	69.06	27.94	22.41
	At most 7	59.53	46.65	22.38	14.89
	At most 8	37.16	31.75	13.51	10.03
	At most 9	23.64	21.72	9.88	9.35
	At most 10	13.76	12.38	7.57	6.79
	At most 11	6.20	5.58	6.19	5.58
1994-2000	None	597.11 [a]	204.01 [a]	214.82 [a]	193.81 [a]
	At most 1	393.11 [a]	189.41 [a]	160.83 [a]	129.77 [a]
	At most 2	203.69	47.52	81.46 [a]	46.38
	At most 3	156.18	43.64	39.24	33.54
	At most 4	112.54	30.26	35.36	29.06
	At most 5	82.28	24.69	34.17	24.53
	At most 6	57.59	19.56	30.46	15.48
	At most 7	38.03	15.41	19.96	12.70
	At most 8	22.63	12.61	19.07	6.84
	At most 9	10.02	6.83	11.69	3.19
	At most 10	3.19	3.19	11.16	0.03
2001-2005	None	644.94 [a]	430.80 [a]	212.28 [a]	103.59 [a]
	At most 1	432.66 [a]	327.22 [a]	118.16 [a]	82.02 [a]
	At most 2	314.49 [a]	245.20 [a]	72.94 [a]	54.35
	At most 3	241.56 [a]	190.85	56.98	49.11
	At most 4	184.58	141.74	49.37	40.54
	At most 5	135.20	101.20	44.05	29.70
	At most 6	91.15	71.50	25.43	23.44
	At most 7	65.72	48.06	19.84	17.68
	At most 8	45.88	30.37	18.92	11.89
	At most 9	26.96	18.48	14.79	9.65
	At most 10	12.17	8.83	7.14	7.78
	At most 11	5.03	1.05	5.03	1.05

Note: [a] significant at the 5% level. CE is referred to the number of cointegrating equations. This table presents the results for twelve currencies. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion to determine the number of lags. The lags were 4, 2 and 4 for the no trend specification and 4, 4 and 4 for the trend specification. The (nonstandard) critical values are taken from Osterwald-Lenum (1992). Costa Rica and Nicaragua are not included. Argentina is not included for the 1994-2000 period.

Table 4. Bivariate Daily Estimates for Unrestricted Cointegration Rank Test.

		BR	*BO*	*CH*	*CO*	*GU*	*ME*	*PA*	*PE*	*RD*	*UR*	*AR*
1994-2005	Brazil	---										
	Bolivia	72.35 [a]	---									
	Chile	145.25 [a]	15.70	---								
	Colombia	116.09 [a]	14.98	13.19	---							
	Guatemala	147.42 [a]	17.14	11.64	8.80	---						
	Mexico	109.47 [a]	11.78	15.43	8.33	14.24	---					
	Paraguay	119.04 [a]	16.74	16.32	6.36	9.30	12.85	----				
	Peru	101.37 [a]	13.39	15.34	19.94 [a]	14.36	35.99 [a]	12.10	---			
	D. Republic	99.09 [a]	13.25	10.04	14.15	8.24	12.71	15.39	10.94	---		
	Uruguay	83.08 [a]	12.65	13.26	9.23	15.93	15.33	20.03 [a]	13.41	15.65	---	
	Venezuela	142.69 [a]	8.93	6.97	7.07	9.69	14.02	7.68	18.08	7.85	9.73	
1994-2000	Brazil	---										
	Bolivia	75.25 [a]	---									
	Chile	96.30 [a]	13.36	---								
	Colombia	57.93 [a]	23.22 [a]	14.31	---							
	Guatemala	73.14 [a]	15.42	10.18	10.16	---						
	Mexico	94.03 [a]	20.24	12.31	14.90	7.92	---					
	Paraguay	85.03 [a]	15.05	9.04	8.28	8.71	10.30	----				
	Peru	105.31 [a]	14.75	9.86	10.35	9.02	33.21 [a]	11.42	---			
	D. Republic	75.22 [a]	15.30	8.03	6.89	12.70	7.53	13.03	8.86	---		
	Uruguay	52.91 [a]	21.71 [a]	22.51 [a]	27.0 [a]	18.78	21.07 [a]	21.71 [a]	18.77	18.43	---	
	Venezuela	79.02 [a]	9.41	9.68	13.04	10.59	8.47	7.54	7.17	14.73	17.77	
2001-2005	Brazil	---										18.05
	Bolivia	12.53	---									13.62
	Chile	4.05	10.09	---								19.38
	Colombia	8.74	20.56 [a]	13.56	---							23.54 [a]
	Guatemala	9.81	16.52	11.48	8.24	---						20.67 [a]
	Mexico	4.07	15.38	15.19	13.98	10.47	---					22.03 [a]
	Paraguay	11.64	20.11	10.82	19.94 [a]	10.75	10.04	---				14.19
	Peru	16.42	15.79	9.28	9.10	8.45	26.93 [a]	6.07	----			12.04
	D. Republic	6.59	12.12	8.68	10.41	6.24	10.01	9.05	6.06	---		4.52
	Uruguay	7.13	26.78 [a]	10.88	24.72 [a]	11.20	16.17	14.09	10.23	9.51	---	19.38 [a]
	Venezuela	17.78	14.78	5.99	23.63 [a]	9.00	15.23	10.14	12.34	19.38	15.29	26.59 [a]

Note: [a] significant at the 5% level. Results are based on the Maximum Eigenvalue Statistic. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion to determine the number of lags. The (nonstandard) critical values are taken from Osterwald-Lenum (1992). The variable mnemonics are as follows: Argentina (AR), Bolivia (BO), Brazil (BR), Colombia (CO), Chile (CH), Guatemala (GU), Mexico (ME), Paraguay (PA), Peru (PE), Dominican Republic (RD), Uruguay (UR) and Venezuela (VE). Argentina is only included in the cointegration tests for the period 2001-2005.

Table 5. Weekly Estimates: Unrestricted Cointegration Rank Test (1/4/1994 – 2/8/2005).

Ho:	*Trace*		λ_{max}	
# of CE(s)	With Trend	Without Trend	With Trend	Without Trend
None	541.27 [a]	470.83 [a]	132.88 [a]	131.68 [a]
At most 1	408.38 [a]	339.15 [a]	109.68 [a]	95.64 [a]
At most 2	298.70 [a]	243.50 [a]	61.27	58.17
At most 3	237.43 [a]	185.33	57.52	50.58
At most 4	179.92	134.75	50.46	36.50
At most 5	129.45	98.25	35.23	30.89
At most 6	94.23	67.36	29.11	22.22
At most 7	65.12	45.14	21.76	15.26
At most 8	43.36	29.88	15.26	13.61
At most 9	28.10	16.27	13.59	8.11
At most 10	14.51	8.16	7.98	6.59

Note: [a] significant at the 5% level. CE is referred to the number of cointegrating equations. This Table presents the results for eleven countries. Countries that are not included are: Argentina, Nicaragua and Costa Rica. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion to determine the number of lags. The lags were 4 for the no trend specification and 2 for the trend specification. The (nonstandard) critical values are taken from Osterwald-Lenum (1992).

Table 6. Bivariate Weekly Estimates for Unrestricted Cointegration Rank Test.

	AR	*BR*	*BO*	*CH*	*CO*	*GU*	*JA*	*ME*	*PA*	*PE*	*RD*	*UR*	*VE*
Argentina	---												
Brazil	21.61 [a]	---											
Bolivia	4.22	41.40 [a]	---										
Chile	7.90	54.83 [a]	12.36	---									
Colombia	2.96	48.26 [a]	9.20	7.64	---								
Guatemala	6.88	39.68 [a]	9.21	8.24	10.44	---							
Mexico	13.25	20.28 [a]	12.81	13.27	12.70	14.19	13.27	---					
Paraguay	4.34	53.92 [a]	9.55	7.55	4.33	7.12	10.93	13.38	---				
Peru	6.97	28.97 [a]	7.57	9.00	11.13	10.71	8.85	11.91	7.67	----			
D. Republic	8.06	19.06	12.06	6.68	7.28	4.72	5.86	12.85	14.98	7.57	---		
Uruguay	15.67 [a]	30.46 [a]	7.52	8.87	3.81	11.88	5.55	14.23	9.85	6.73	10.42	---	
Venezuela	9.06	21.03 [a]	9.50	5.84	5.62	9.37	12.27	13.53	7.96	6.24	5.88	10.39	---

Note: [a] significant at the 5% level. Results are based on the Maximum Eigenvalue Statistic. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion to determine the number of lags. The variable mnemonics are as follows: Argentina (AR), Bolivia (BO), Brazil (BR), Colombia (CO), Chile (CH), Guatemala (GU), Mexico (ME), Paraguay (PA), Peru (PE), Dominican Republic (RD), Uruguay (UR) and Venezuela (VE). The (nonstandard) critical values are taken from Osterwald-Lenum (1992).

Table 7. Daily Estimates for the Cointegration Test: Maximum Eigenvalue and Trace Statistics by Trade Areas for the 1994-2005 period.

			Trace		λ_{max}	
	Ho: No. of CE(s)	Lags	With Trend	Without Trend	With Trend	Without Trend
Mercosur	None	4	185.73 [a]	165.71 [a]	124.30 [a]	124.35 [a]
	At most 1		61.43 [a]	41.36 [a]	37.91 [a]	33.10 [a]
	At most 2		23.51	8.26	19.28	7.97
	At most 3		4.23	0.28	4.23	0.28
Mercosur and Chile	None	8	193.44 [a]	208.55 [a]	113.03 [a]	149.37 [a]
	At most 1		80.41 [a]	59.18 [a]	46.38 [a]	37.19 [a]
	At most 2		34.02	21.99	23.77	10.59
	At most 3		10.25	11.40	7.78	8.45
	At most 4		2.48	2.95	2.48	2.95
Mercosur, Chile and Bolivia	None	2	312.28 [a]	233.91 [a]	214.43 [a]	150.87 [a]
	At most 1		97.84 [a]	83.05 [a]	48.99 [a]	39.88 [a]
	At most 2		48.85 [a]	43.17	29.21 [a]	25.78
	At most 3		19.63	17.40	9.91	8.87
	At most 4		9.72	8.52	6.20	5.55
	At most 5		3.52	2.97	3.52	2.97
G3	None	2	26.65	27.32	13.19	13.50
	At most 1		13.44	13.82	11.59	11.89
	At most 2		1.85	1.93	1.85	1.93
LAIA Area	None	2	616.19 [a]	415.52 [a]	247.27 [a]	177.19 [a]
	At most 1		368.92 [a]	238.38 [a]	133.78 [a]	79.828 [a]
	At most 2		235.14 [a]	158.49	80.73 [a]	52.17
	At most 3		154.41 [a]	106.33	50.06	36.37
	At most 4		104.35	69.95	35.93	21.83
	At most 5		68.42	48.13	25.31	17.44
	At most 6		43.11	30.69	18.02	14.18
	At most 7		25.09	16.51	13.57	7.44
	At most 8		11.52	9.07	7.19	5.70
	At most 9		4.33	3.38	4.33	3.38
Andean Group	None		62.29	50.69 [a]	30.36	29.19 [a]
	At most 1	4	31.93	21.50	10.07	9.47
	At most 2		21.86	12.03	8.38	7.46
	At most 3		13.47	4.57	7.46	4.57
CAFTA	None		20.63	1635.80 [a]	12.93	1626.34 [a]
	At most 1	6	7.70	9.46	4.23	6.15
	At most 2		3.47	3.30	3.473	3.30

Note: [a] significant at the 5% level. CE is referred to the number of cointegrating equations. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion in the determination of the number of lags. The (nonstandard) critical values are taken from Osterwald-Lenum (1992)

Table 8. Weekly Estimates for the Cointegration Test: Maximum Eigenvalue and Trace Statistics by Trade Areas for the 1994-2005 period.

			Trace		λ_{max}	
	Ho: No. of CE(s)	Lags	With Trend	Without Trend	With Trend	Without Trend
Mercosur	None	2	91.80 [a]	137.88 [a]	59.32 [a]	73.79 [a]
	At most 1		32.48 [a]	64.09 [a]	23.19 [a]	37.64 [a]
	At most 2		9.29	26.46 [a]	9.12	22.72 [a]
	At most 3		0.18	3.74	0.18	3.74
Mercosur and Chile	None	4	120.90 [a]	148.34 [a]	65.33 [a]	90.63 [a]
	At most 1		55.57 [a]	57.72 [a]	31.99 [a]	38.17 [a]
	At most 2		23.58	19.55	11.75	10.29
	At most 3		11.83	9.26	10.88	7.84
	At most 4		0.95	1.43	0.95	1.43
Mercosur, Chile and Bolivia	None	2	141.97 [a]	212.59 [a]	66.10 [a]	95.42 [a]
	At most 1		75.87 [a]	117.17 [a]	33.91 [a]	58.83 [a]
	At most 2		41.96	58.34	20.79	27.28
	At most 3		21.17	31.06	12.03	19.19
	At most 4		9.14	11.88	8.55	8.59
	At most 5		0.58	3.28	0.58	3.28
G3	None	2	24.37	29.11	14.25	14.77
	At most 1		10.12	14.34	7.83	10.02
	At most 2		2.29	4.32	2.29	4.32
LAIA Area	None		302.56 [a]	393.97 [a]	90.49	124.75 [a]
	At most 1		212.08 [a]	269.22 [a]	59.57	73.72 [a]
	At most 2	6	152.51	195.49 [a]	33.53	51.42
	At most 3		118.98	144.07	29.91	44.70
	At most 4		89.07	99.37	25.66	33.02
	At most 5		63.41	66.35	20.85	22.85
	At most 6		42.56	43.50	16.28	15.47
	At most 7		26.28	28.03	11.39	13.52
	At most 8		14.90	14.51	8.97	8.51
	At most 9		5.93	5.99	5.93	5.99
Andean Group	None		82.55	71.31 [a]	25.38	21.19
	At most 1	4	57.17	50.12 [a]	20.45	15.40
	At most 2		36.72	34.72 [a]	15.40	15.05
	At most 3		21.32	19.66 [a]	14.28	12.62

Note: [a] significant at the 5% level. CE is referred to the number of cointegrating equations. The number of lags was determined from a VAR specification with the property of white noise residuals. We used the SIC criterion in the determination of the number of lags. The (nonstandard) critical values are taken from Osterwald-Lenum (1992)

Table 9. TR^2 Statistics: ARCH tests of Daily Dollar Return, January 3, 1994 – February 8, 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-SA (2)*
Argentina	12.90 [a]	13.25 [a]	40.67 [a]	40.67 [a]	48.03 [a]	86.81 [a]	6.67 (2.89) [c]	14.28 (1.66)	15.70 [a] (6.81) [a]	16.67 (3.35) [a]
Bolivia	380.61 [a]	529.38 [a]	689.30 [a]	697.82 [a]	751.12 [a]	833.28 [a]	12.83 [a] (4.17) [a]	293.74 [a] (31.34) [a]	270.38 [a] (20.18) [a]	294.38 [a] (1.17)
Brazil	269.58 [a]	293.38 [a]	309.59 [a]	309.49 [a]	310.43 [a]	310.07 [a]	122.57 [a] (50.67) [a]	530.38 [a] (2.53)	406.06 [a] (29.38) [a]	886.52 [a] (16.48) [a]
Chile	453.01 [a]	488.80 [a]	511.01 [a]	519.72 [a]	534.87 [a]	546.64 [a]	405 [a] (158.06) [a]	551.30 [a] (103.41) [a]	516.03 [a] (76.31) [a]	571.73 [a] (42.98) [a]
Colombia	175.42 [a]	222.48 [a]	244.42 [a]	253.43 [a]	265.59 [a]	271.65 [a]	181.30 [a] (71.90) [a]	279.30 [a] (45.00) [a]	232.96 [a] (26 .68) [a]	291.39 [a] (17.34) [a]
Guatemala	206.06 [a]	212.07 [a]	215.51 [a]	220.54 [a]	241.10 [a]	245.26 [a]	207.45 [a] (50.28) [a]	213.78 [a] (31.65) [a]	176.52 [a] (20.58) [a]	180.62 [a] (12.59) [a]
Mexico	165.47 [a]	554.81 [a]	563.33 [a]	629.15 [a]	633.31 [a]	667.34 [a]	165.71 [a] (10.31) [a]	555.21 [a] (8.61) [a]	166.70 [a] (8.02) [a]	666.84 [a] (4.96) [a]
Paraguay	154.42 [a]	159.10 [a]	166.60 [a]	166.56 [a]	179.08 [a]	179.42 [a]	21.15 [a] (13.70) [a]	159.49 [a] (8.53) [a]	185.79 [a] (6.49) [a]	424.56 [a] (2.42) [a]
Peru	90.83 [a]	109.11 [a]	467.04 [a]	471.26 [a]	526.79 [a]	539.23 [a]	65.47 [a] (23.07) [a]	109.52 [a] (14.69) [a]	98.66 [a] (11.08) [a]	118.29 [a] (8.82) [a]
D. Republic	624.17 [a]	625.34 [a]	627.15 [a]	635.68 [a]	640.47 [a]	646.10 [a]	624.50 [a] (21.00) [a]	625.97 [a] (12.96) [a]	628.42 [a] (8.67) [a]	120.77 [a] (4.88) [a]
Uruguay	151.35 [a]	609.74 [a]	644.07 [a]	644.28 [a]	833.50 [a]	880.91 [a]	36.68 [a] (13.58) [a]	610.30 [a] (8.54) [a]	164.07 [a] (7.86) [a]	627.15 [a] (3.37) [a]
Venezuela	4.71 [b]	4.71	4.71	4.71	4.75	4.78	4.8 (2.47) [c]	5.01 (1.50)	5.05 (1.82)	5.86 (1.34)
5% CV for TR^2 (χ^2)	3.84	5.99	7.81	9.49	15.51	21.03	9.49	15.51	15.51	26.30

Note: [a, b] and [c] indicate significance at the 1%, 5% and 10% 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 (as a proxy of volatility) on a constant and lags of own squares. The test distribution is $\chi 2$ with degrees of freedom p = 1, 2, 3, 4, 8 and 12. (i.e. ARCH(1) indicates univariate ARCH with one lag while ARCH(12) reveals univariate ARCH with 12 lags.) The Multivariate test is an ARCH test with a multivariate information set. The test is conducted by regressing the squared currency return (row), on a constant, lag of its own and lags of other currency returns. 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. The numbers in parenthesis give the Wald test statistic for the significance of exogenous variables.

Table 10. Common ARCH Feature test for Daily Data: January 3, 2001 – February 8, 2005

Countries	Min TR2	λ	ARCH (4)	MARCH-NCA (1)	MARCH-SA(1)
Bolivia/Brazil	3.76	-0.6	101.51 [a]	115.38 [a]	105.05 [a]
Brazil/Chile	0.61	0.01	247.35 [a]	257.26 [a]	264.68 [a]
Brazil/Colombia	1.10	0.2	258.97 [a]	261.05 [a]	262.31 [a]
Brazil/Paraguay	2.02	-0.17	270.35 [a]	272.71 [a]	271.37 [a]
Brazil/Uruguay	1.62	0.04	241.37 [a]	243.78 [a]	246.74 [a]
Chile/Paraguay	10.88	1.51	41.48 [a]	42.01 [a]	49.42 [a]
Chile/Uruguay	11.40	-1.94	203.28 [a]	203.64 [a]	244.75 [a]
Colombia/Paraguay	2.87	-0.47	182 [a]	182.39 [a]	183.45 [a]
Paraguay/Uruguay	0.84	0.18	62.78 [a]	63.16 [a]	73.00 [a]
5% CV for TR^2 (χ^2)	21.03		9.49	15.51	21.03

Note: [a] 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 ($x_{1t} * x_{2t}$)). 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.

Table 11. TR^2 Statistics: ARCH tests of Weekly Dollar Return, January 3, 1994 – February 8, 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 [a]	29.90 [a]	29.86 [a]	30.17 [a]	30.57 [a]	56.71 [a]	3.93 (1.44)	4.07 (1.12)	31.25 [a] (0.69)	31.89 [a] (0.69)
Bolivia	144.23 [a]	188.69 [a]	211.04 [a]	224.11 [a]	243.23 [a]	246.97 [a]	3.23 (0.76)	3.67 (0.60)	146.3 [a] (0.65)	121.26 [a] (0.54)
Brazil	233.79 [a]	233.59 [a]	234.51 [a]	232.73	249.84 [a]	241.43 [a]	41.69 [a] (12.32) [a]	42.27 [a] (7.72) [a]	242 [a] (2.83) [a]	252.43 [a] (2.65) [a]
Chile	108.94 [a]	110.10 [a]	117.77 [a]	118.20 [a]	133.99 [a]	134.62 [a]	110 [a] (34.09) [a]	128.3 [a] (21.72) [a]	117.21 [a] (14.46) [a]	121.46 [a] (8.19) [a]
Colombia	102.79 [a]	108.53 [a]	112.22 [a]	113.07 [a]	118.21 [a]	118.64 [a]	96.11 [a] (29.26) [a]	97.12 [a] (17.24) [a]	106.28 [a] (17.05) [a]	130.72 [a] (8.38) [a]
Guatemala	83.15 [a]	83.10 [a]	83.09 [a]	83.37 [a]	87.68 [a]	88.41 [a]	84.01 [a] (22.59) [a]	84.49 [a] (9.71) [a]	73.36 [a] (15.05) [a]	82.53 [a] (7.70) [a]
Mexico	114.25 [a]	120.10 [a]	129.80 [a]	130.12 [a]	145.95 [a]	194.66 [a]	114.56 [a] (4.83) [a]	120.3 [a] (2.80) [a]	37.70 [a] (3.68) [a]	39.89 [a] (2.65) [a]
Paraguay	106.03 [a]	116.00 [a]	123.36 [a]	125.93 [a]	134.02 [a]	143.60 [a]	44.47 [a] (15.78) [a]	44.72 [a] (9.51) [a]	111.6 [a] (4.43) [a]	128.60 [a] (2.35) [a]
Peru	141.83 [a]	142.84 [a]	148.16 [a]	147.92 [a]	148.27 [a]	151.44 [a]	58.25 [a] (16.84) [a]	63.95 [a] (12.04) [a]	149.19 [a] (9.26) [a]	159 [a] (2.92) [a]
D. Republic	48.62 [a]	48.65 [a]	58.40 [a]	65.97 [a]	74.33 [a]	90.73 [a]	49.31 [a] (8.35) [a]	49.70 [a] (4.57) [a]	58.74 [a] (3.83) [a]	60.92 [a] (2.25) [a]
Uruguay	187.98 [a]	200.44 [a]	200.25 [a]	217.27 [a]	272.41 [a]	289.80 [a]	23.32 [a] (8.91) [a]	23.49 [a] (5.90) [a]	200.99 [a] (1.70) [c]	229.92 [a] (1.99) [a]
Venezuela	5.08 [a]	5.08	5.10	5.11	5.17	5.28	5.15 (2.29) [c]	5.42 (1.37)	5.36 (2.41) [a]	6.15 [a] (1.17)
5% CV(χ^2)	3.84	5.99	7.81	9.49	15.51	21.03	7.81	12.59	16.92	28.87

Note: [a], indicates significance at the 5% 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 $\chi 2$ with degrees of freedom p = 1, 2, 3, 4, 8 and 12. (i.e. ARCH(1) indicates univariate ARCH with one lag) The Multivariate test is an ARCH test with a multivariate information set. The test is conducted by regressing the squared currency return (row), on a constant, lag of its own and lags of other currency returns. 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. The numbers in parenthesis give the Wald test statistic for the significance of exogenous variables.

Table 12. Univariate GARCH (1,1) Estimates

	a_0	a_1	a_2	ω	α	β	*Wald Test* H_0: $\alpha+\beta=1$
Argentina	0.0007			5.07e-05	0.036	0.878 [a]	11.4
	(0.0007)			(3.58e-05)	(0.039)	(0.049)	
Bolivia	0.100 [a]	0.016		-0.0009	0.663 [a]	0.715 [a]	4.24 [b]
	(0.012)	(0.169)		(0.007)	(0.483)	(0.017)	
Brazil	0.0015 [a]	0.234 [a]		1.24e-05	0.283 [a]	0.726 [a]	2.86 [c]
	(0.0005)	(0.057)		(1.14e-05)	(0.084)	(0.051)	
Chile	0.037	0.083 [c]	0.085 [c]	0.013 [c]	0.104 [a]	0.894 [a]	1.98
	(0.037)	(0.043)	(0.049)	(0.008)	(0.033)	(0.032)	
Colombia	0.079 [a]	0.074	0.119 [a]	0.175 [a]	0.382 [a]	0.514 [a]	2.81 [c]
	(0.038)	(0.048)	(0.048)	(0.034)	(0.065)	(0.064)	
Guatemala	0.00015	0.131 [a]		1.35e-06 [a]	0.169 [a]	0.789 [a]	1.11
	(0.0002)	(0.055)		(5.33e-07)	(0.048)	(0.059)	
Mexico	0.147 [a]	0.062		0.568	0.160	0.619 [a]	2.20 [c]
	(0.061)	(0.059)		(0.626)	(0.162)	(0.293)	
Paraguay	0.081 [a]	0.211 [a]		0.003 [a]	0.597 [a]	0.684 [a]	1.68
	(0.017)	(0.075)		(0.002)	(0.143)	(0.049)	
Peru	0.018	0.157 [a]		0.057 [a]	0.524 [a]	0.389 [a]	2.62 [c]
	(0.020)	(0.045)		(0.015)	(0.154)	(0.095)	
Dom. Rep.	0.055 [a]	0.114 [c]		0.002	0.250 [a]	0.850 [a]	5.84 [a]
	(0.024)	(0.065)		(0.003)	(0.072)	(0.055)	
Uruguay	0.327 [a]			0.010 [a]	0.677 [a]	0.628 [a]	1.25
	(0.020)			(0.006)	(0.183)	(0.040)	

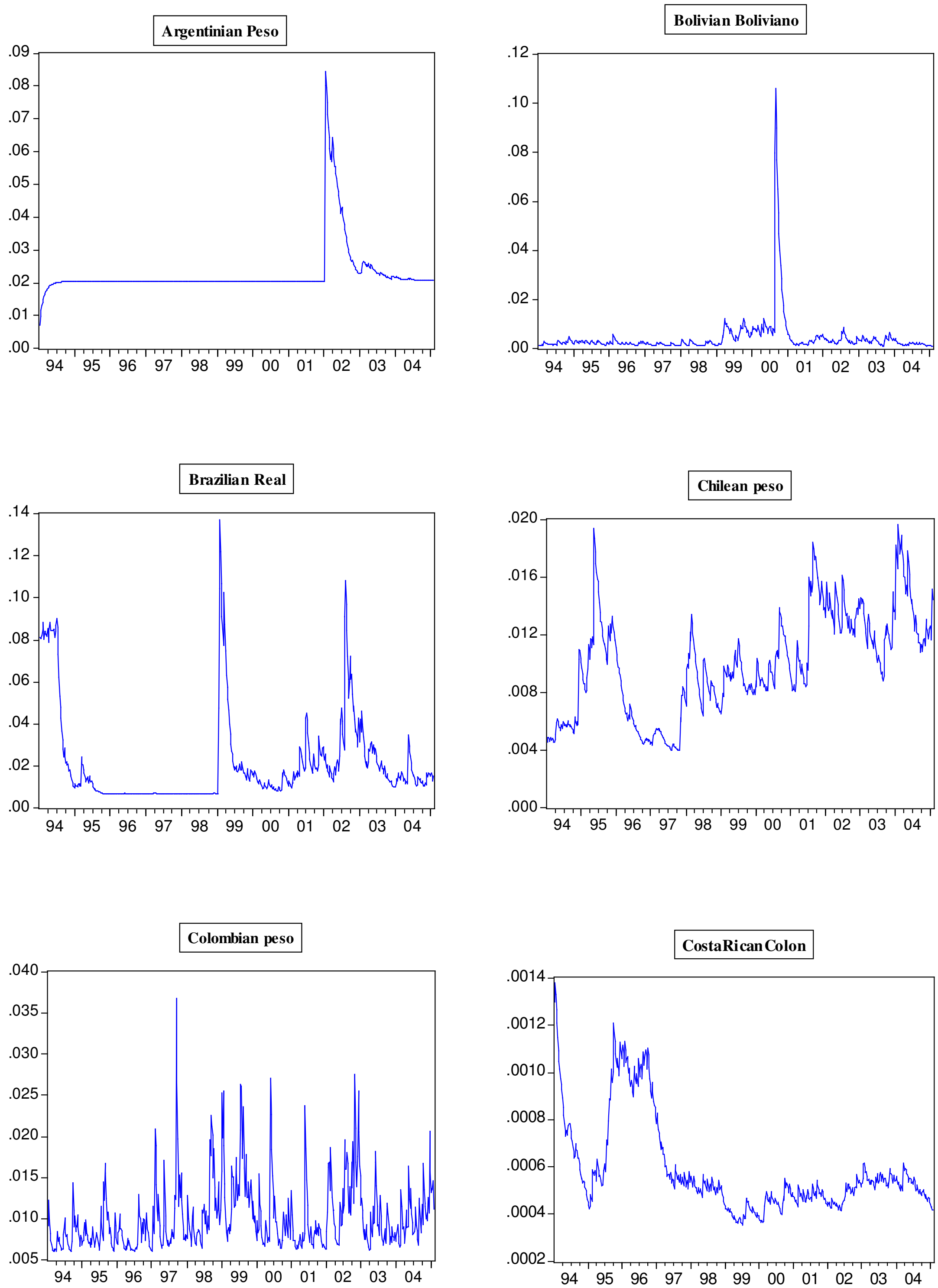
Note: [a, b] and c indicate significance at the 1%, 5% and 10% level respectively. Numbers in parenthesis are robust standard errors Bollerslev and Wooldridge (1992). The reported quasi-maximum likelihood estimates of univariate generalized autoregressive conditional heteroscedastic GARCH models are of the form $x_{it} = f(x_i; ß) + u_t$, where, $u_t/\psi_{t-1} \sim \mathbf{N}(0, h_t^2)$. We specify the mean equation as either an AR (1), an AR(2) process or having a constant mean. We want to concentrate mainly on the variance process.

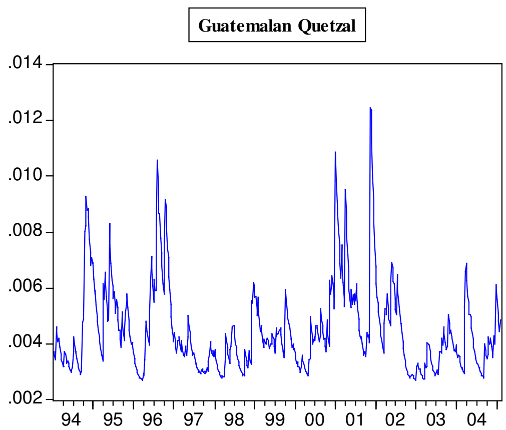
Table 13. Common ARCH Feature Test for Weekly Data

Countries	Min TR2	λ	ARCH (4)	MARCH (4)					
				Ar	Br	Ch	Co	Pa	Ur
Argentina/ Uruguay	9.11	0.84	5.43	6.11	5.77	9.05	5.59	5.87	6.47
Argentina/Colombia	6.08	0.25	3.01	18.49 [a]	18.13 [a]	21.50 [a]	18.31 [a]	18.04 [a]	18.10 [a]
Argentina/Guatemala	16.08	0.08	12.07 [a]	27.27 [a]	26.88 [a]	30.12 [a]	27.15 [a]	26.78 [a]	26.88 [a]
Chile/Brazil	15.36	-0.05	10.82	13.68	12.12	30.61 [a]	13.97	14.35	13.01
Chile/Colombia	8.86	-0.67	2.01	3.16	3.25	15.35	3.27	3.72	3.23
Chile/Guatemala	16.37	-0.38	9.40	12.58	10.99	31.22 [a]	12.18	14.09	12.33
Chile/Paraguay	15.31	0.06	12.11 [a]	14.19	14.14	32.28 [a]	14.97	16.04 [a]	14.25
Chile/Peru	10.83	-0.7	5.46	8.53	8.19	25.01 [a]	8.09	10.07	8.21
Chile/Uruguay	14.16	0.01	11.89 [a]	14.74	13.61	32.37 [a]	14.77	15.62	14.70
Colombia/Guatemala	13.68	0.34	4.15	5.06	6.09	6.58	5.30	7.47	5.97
Colombia/Dominican Republic	18.83	-0.2	13.64 [a]	16.89 [a]	14.26	16.18 [a]	19.25 [a]	20.90 [a]	31.02 [a]
Guatemala/Paraguay	20.18	-0.09	15.43 [a]	15.52 [a]	17.47 [a]	16.99 [a]	16.91 [a]	17.22 [a]	23.68 [a]
Guatemala/Peru	18.53	0.19	21.82 [a]	22.108 [a]	23.90 [a]	23.05 [a]	23.51 [a]	24.18 [a]	28.89 [a]
Guatemala/Dominican Republic	17.58	0.07	10.59	10.93	13.38	13.20	12.24	13.02	15.91 [a]
5%CV	21.03		9.49			15.51			

Note: [a] 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 ($x_{1t} * x_{2t}$)). Venezuela is excluded from the sample, as it does not display ARCH. ARCH (4) is referred to an ARCH test of the portfolio $y(\lambda)$ on four own lags. The MARCH test (multivariate) additionally includes four lags of other currencies that might contain some explanatory power about the volatility process. The variable mnemonics are as follows: Argentina (AR), Brazil (BR), Colombia (CO), Chile (CH), Paraguay (PA), and Uruguay (UR).

Figure 2. Conditional Volatility of Latin American Currencies: Weekly Data, 1994-2005.

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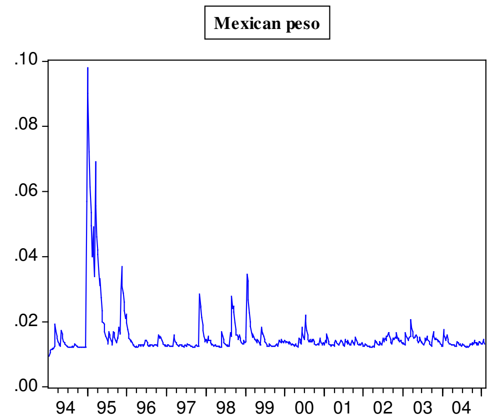
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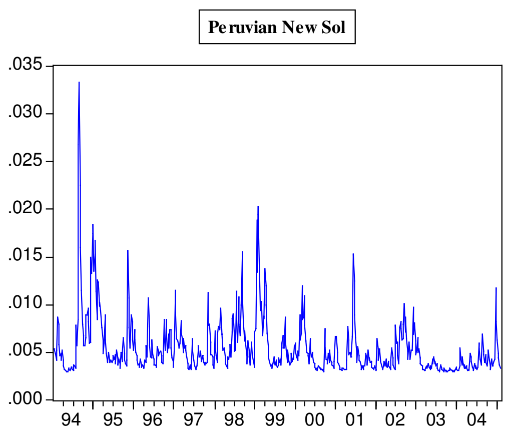
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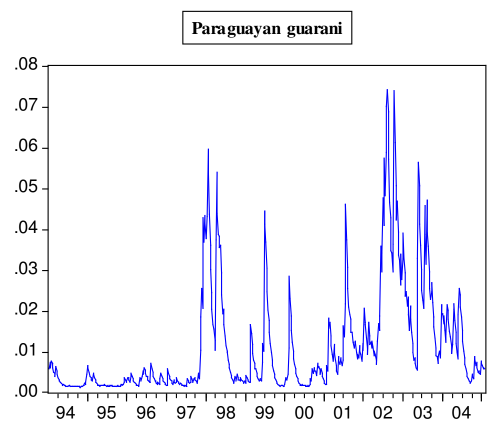
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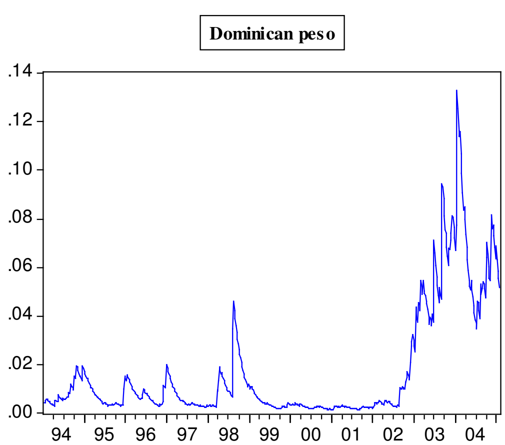
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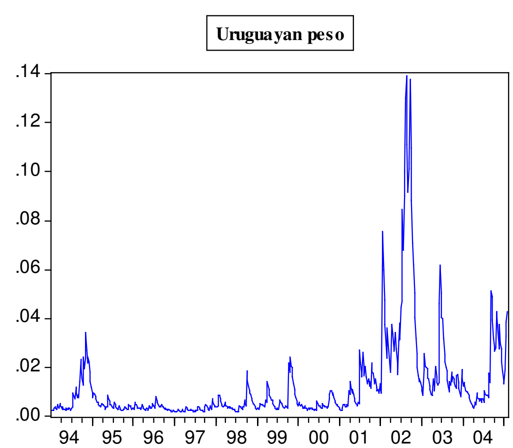
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