Interdependence in conditional variances between Latin American stock markets

Vanderlei Kleinschmidt

Professor of the Economics Department at FURB (Universidade Regional de Blumenau).

e-mail: vanderleik@yahoo.com.br

Address:
Rua Alberto Koffcke 300, ap. 102
Velha
89.012-440 – Blumenau (SC)

Roberto Meurer

Professor of the Department of Economics at UFSC (Universidade Federal de Santa Catarina).

e-mail: robertomeurer@yahoo.com

Address:
Departamento de Economia
Centro Sócio Econômico
UFSC
88.040-900 – Florianópolis (SC)

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This paper aims to identify the relationships between the conditional variance and co-movements of the returns of Latin American (Argentina, Brazil and Mexico) stock markets. Exponential GARCH and multivariate GARCH (BEKK) models are estimated to find asymmetrical effects on innovation shocks. The results show high sensitivity of the Granger causality test to lags, indicating that it should not be used as the only measure for causal relationships or precedence in the conditional variance between the stock markets. We find a positive relationship between risk and returns in the Latin American markets and a negative relationship with the Dow Jones index. Market returns have shown high persistence in their conditional variance. The existence of co-movements in the conditional variances of the stock markets is also pointed out. The inclusion of the international market and asymmetry in the estimation leads to more robust results.

Key words: Exponential GARCH, BEKK, Latin American stock markets, conditional variance.
JEL classification: C32, C22, G11.

1. Introduction

This paper aims to identify precedence relationships in the volatility of the returns of three Latin American stock market indexes. Univariate and multivariate autoregressive conditional heteroskedasticity tools are employed, in order to understand the channels by which such volatility is transmitted between these markets. These relationships are of interest to market analysts and policy makers and favored by the developments of time series econometrics applied to modern finance theory.

Since markets are more integrated, information in one country can influence other markets (Felipe and Diranzo 2005). These links between local and global markets reduce market segmentation, but some inefficiency remains in the stock markets. Three hypotheses seek to explain transmission or contagion between integrated markets: liberalization, capital flows, and companies that are traded in more than one market.

The liberalization of stock markets leads to a strong link between international markets, lowering transaction costs and increasing liquidity, but can also bring higher volatility, which can lead to a financial crisis. Several studies analyze the effects of stock market liberalization on local market volatility. Bekaert and Harvey (1997) show that liberalization of capital markets increases the relationship between returns in the local and global market. Bekaert and Harvey (2000) find a small increase in volatility after stock market liberalization. The majority of studies in this area show that stock markets become more volatile after liberalization, especially emerging markets (Levine and Zervos, 1998; Singh and Weisse, 1998; Cha and Oh, 2000).

There is a perception that foreign speculators are the first to withdraw from a market in the case of instability, reducing liquidity in stock markets. A higher presence of speculators in emerging markets can lead to a crisis, destabilizing these markets (Froot, O'Connell and Seasholes, 2001; Sarno and Taylor, 1999; Carstens and Schwartz, 1998; Grabel, 1996).

Cross listing is one of the linkages between stock markets. It allows for investment diversification, an increase of financial and economic ties, and can attract new capital, which increases the market value of a company and is positive for stockholders (Sabri, 2002; Doukas and Switzer, 2000). However, cross listing may allow for greater inefficiency in the market, because the company is listed and priced in different currencies, pricing methods, regulatory laws, thus contributing to great volatility (Froot and Dabora, 1999; Hargis, 2000; Domowitz, Glen, and Madhavan, 1998).

Initial studies of volatility transmission indicate the existence of degrees of interdependence between markets, which lead them to move together (Eun and Shim, 1989). These transmissions happen in markets globally, in regions, in pairs of markets, and in markets with similar patterns. It seems there is more interdependence between volatilities than in returns. The common persistence has important implications on the linkages between prices and also on the choice of optimal portfolios (Bollerslev and Engle, 1993). Furthermore, hedge portfolios are a good example in which future variance and conditional variance between assets has an important role (Bollerslev, Chou and Kroner, 1992).

Volatility transmission can happen in three ways: high correlations between stock market indexes (indexes become integrated and prices change together), intraday volatility transmission (a fall in volatility can occur in the beginning, during, or after market hours), and the influence of leading markets (followed by other markets).

High correlation between markets leads to an environment of high risk in times of high volatility and falling prices. High correlation appears between developed markets, emerging markets, pairs of markets, and among the indexes of developed and emerging markets (Ball and Torous, 2000; Solnik, Boucrelle and Le Fur, 1996; Bracker and Koch, 1999).

Bracker and Koch (1999) show that the matrix of correlations between international markets changes over time. Fasolo (2006) finds evidence of contagion only during the crisis of 1997 and 1998 in Asia and Russia. Jeonh (1999) finds that the domestic market is affected by surprises in the volatility in domestic and in foreign markets.

Intraday transmission happens between markets and the co-movements of prices are due to the daily information flow. These relations are reciprocal and transmitted from one market to the other. Kane, Lehmann and Trippi (2000) find that volatility increases after a change in prices but returns to its former level after one or two weeks. Chan, Chockalingam and Lai (2000) find that intraday volatility is higher at the beginning of the day and diminishes at noon. The co-movements for a given pair of stock markets can change over time (Bracker, Docking and Koch, 1999).

United States, Japanese, and London markets lead the others. There are also regional markets that behave as leaders in a region or markets with similar patterns. The US market is the leader, followed by the other markets (Janakiramanan and Lamba, 1998; Kearney, 2000). The Japanese market also has an influence (Wu and Su, 1998).

The concept of contagion is not unanimous between researchers. It can be defined as what happens when a shock in one country is transmitted to another one even when there is not a sensible change in the relationship between them. In other cases it is the heightening of the linkages between markets after a shock in one of the countries (Forbes and Rigobon, 2002). It is important to understand the dynamics of the contagion because of the linkages by which the shocks are transmitted, such as trade and finance (Dornbusch, Park and Claessens, 2000). There is evidence that contagion is more regional than global and literature analyzes the relationship between macroeconomic fundamentals and financial crises, finding that the same fundamentals between countries is a channel for contagion of the other markets (Kaminski and Reinhart, 2000).

Bae, Karolyi and Stulz (2003) present a multinomial logistic regression model to measure the contagion effect. Results indicate that contagion can be forecasted and depends on the regional interest rate, exchange rate, and volatility of the returns in respective stock markets. Extreme negative returns lead to markets which are more prone to contagion than positive values.

Lombardi et al (2004) employ a multivariate model and show that the contagion pattern between Brazilian and Argentinean stock markets change from the 1990s to the first half of the 2000 decade. Araujo (2008) studies the economic sources of the co-movements of real returns of the Latin American stock markets, and identifies three structural shocks:

demand, supply, and portfolio. The last two are the main source behind shocks in returns. Furthermore, supply and demand shocks are weakly correlated between countries, suggesting there is financial integration without economic integration in Latin America.

This paper differs from literature of the area by analyzing how the volatility in the returns in one market influences volatility in another. Univariated and multivariated econometric tools are employed. The analysis is done for the main Latin American stock markets indexes, Ibovespa (Brazil), IPC (Mexico) and Merval (Argentina).

It is important for players in the financial market to understand and model volatility in the stock market. Decisions about investments depend on the evaluation of future returns and risks. The expected volatility of an asset has an important role in the option pricing theory. Finally, correct specification of the volatility of the returns can shed some light on the return generator process (Cao and Tsay, 1992). Thus, this paper aims to answer the following questions: i) what are the relationships between return and risk in Latin American stock markets and which are the asymmetric relationships?; ii) Which is the direction of the precedence relations between the volatility of the stock market returns between Latin American emerging markets and the international markets?; and iii) Is there some evidence of a co-movement of the conditional variance of these markets?

The paper is divided into four sections. The first is this short introduction, the second discusses the econometric models employed, the third shows results and analysis, and section four concludes.

2. Models

Risk averse economic agents need to expect a higher return in order to take risky assets in their portfolios. The relationships between the mean and variance of the returns that will ensure equilibrium depend on the utility function of the agents and the assets' supply conditions (Engle, Lilien and Robins, 1987). For a long time linear time series models were employed to describe the volatility of stock returns (Cao and Tsay, 1992). Patterns like clusters in the volatility series, however, can not be described by linear models, leading to the development of the models of the ARCH family.

2.1. The ARCH-M model

In financial temporal series it is common that the return of an asset depends on its own volatility, which means that agents need a premium in order to maintain risky assets. A model capable of capturing this behavior is the ARCH-M, proposed by Engle, Lilien and Robins (1987). To describe the ARCH-M model, let $\mu_{i,t}$ be the premium demanded by risk averse agents in order to maintain a risky asset *i* during a period *t*. $y_{i,t}$ is the gross return of the asset *i* in one period, and $\varepsilon_{i,t}$ is the difference between ex post and ex ante returns, which is not observable in an efficient market and whose variance conditional to the whole set of information available in the previous period (F_{t-1}) is $h^2_{i,t}$.

$$y_{i,t} = \mu_{i,t} + \varepsilon_{i,t} \quad (1)$$

Assuming that the risk premium is an increasing function of the conditional variance of $\varepsilon_{i,t}$, then a higher conditional variance of the return will demand a higher compensation to the asset holder. It is assumed that the risk of an asset is not diversifiable, implying that only the variance matters. Thus, the risk premium can be expressed as a linear function of the standard deviation:

$$\mu_{i,t} = \beta + \delta h_{i,t} \quad (2)$$

With $\delta > 0$, the changes in the variances are reflected less than proportionally on the mean, increases in the conditional variance are associated with increasing or lowering the conditional mean. The parameter $\mu_{i,t}$ estimates the direct relationship between conditional standard deviation and risk, the tradeoff between risk and return, which depends on the partial derivative of the function $g(\mu_t, h_t; F_{t-1})$ with relation to h_t.

Finally, the variance conditioned to the information available to the investor in t-1 has the form

$$h_t^2 = \alpha_0 + \sum_{i=1}^{r} \alpha_i \varepsilon_{t-j}^2 \quad (3)$$

A problem with the ARCH/GARCH models is the restriction of symmetric effects on the conditional variance function. However, there are also negative correlations between current returns and future volatility. The GARCH models do not consider this, and can so restrict the dynamics of the conditional variance process in the wrong way. There is also a problem with the interpretation of the persistence of the shocks on the conditional variance because of the differences in measuring the persistence (Nelson, 1991).

2.2. The E-GARCH model

Nelson (1991) proposes a new GARCH model to solve these problems and achieve more realistic results in the estimation of the conditional variance of asset returns, the E-GARCH (*Exponential* GARCH). This model relaxes the restriction of the estimation of non-negative coefficients.

If $\sigma_{i,t}^2$ is the conditional variance of $\varepsilon_{i,t}$ given the information available in t-1, it is non-negative with a probability of 1. The GARCH or EGARCH model assures this by making $\sigma_{i,t}^2$ a linear combination with positive weights of the random variables (Nelson, 1991). Another way to do this is making $\ln(\sigma_{i,t}^2)$ linear in some function of the time and the lagged $z_{i,t}$ function.[1] Thus,

$$\ln(\sigma_{i,t}^2) = \alpha_t + \sum_{k=1}^{\infty} \beta_k g(z_{i,t-k}) \quad (4)$$

with $\beta_1 \equiv 1$, $\{\alpha_t\}_{t=-\infty,\infty}$ e $\{\beta_k\}_{k=1,\infty}$ which are real scalar sequences, and not random.

[1] The funcion z relates to: $\varepsilon_{i,t} = \sigma_{i,t} z_{i,t}$ with $z_{i,t} \sim iid(0,1)$. In the conventional ARCH/GARCH models introduced by Engle (1982) and Bollerslev (1986), a linear $\sigma_{i,t}^2$ is employed on the lagged terms of $\varepsilon_{i,t}^2 = \sigma_{i,t}^2 z_{i,t}^2$.

The asymmetric relations between stock returns and changes on the volatility $g\left(z_{i,t}\right)$ is a function of the magnitudes and the signs of $z_{i,t}$. The idea is to make $g\left(z_{i,t}\right)$ a linear combination of $z_{i,t}$ e $\left|z_{i,t}\right|$:

$$g\left(z_{i,t}\right) \equiv \theta z_{i,t} + \gamma\left[\left|z_{i,t}\right| - E\left|z_{i,t}\right|\right] \qquad (5)$$

where $\left\{g\left(z_{i,t}\right)\right\}_{k=-\infty,\infty}$ is a random sequence with zero mean and independently and identically distributed. Its components $\theta z_{i,t}$ and $\gamma\left[\left|z_{i,t}\right| - E\left|z_{i,t}\right|\right]$, are orthogonal in the case of symmetric distribution of $g\left(z_{i,t}\right)$.

An alternative way to express the E-GARCH model is to represent it as:

$$\ln\left(\sigma_{i,t}^2\right) = \omega + \sum_{j=1}^{l} \alpha_j \ln\left(\sigma_{i,t-j}^2\right) + \sum_{j=1}^{m} \beta_j \left|\frac{\varepsilon_{i,t-j}}{\sigma_{i,t-j}}\right| + \sum_{k=1}^{n} \gamma_k \frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}} \qquad (6)$$

where α_j measures the persistence in the conditional variance, β_j links the lagged standardized innovations on the volatility on the symmetric volatility, while γ_k links the lagged standardized innovations on the asymmetric volatility. This implies that a positive or negative shock on the innovations produces a non-expected heightening or lowering on the conditional variance of the assets' returns. In other words, non- anticipated shocks (surprises or news) produce different effects on the conditional variance, whose result can be positive or negative. The impact of such news can be measured by the coefficients β_j e γ_k [2].

One pattern of the model is that it allows us to observe the leverage effect. If $\varepsilon_{i,t-j}/\sigma_{i,t-j}$ is positive, the effect of a shock on the log of the conditional variance is $\sum_{j=1}^{m}\beta_j + \sum_{k=1}^{n}\gamma_k$. If $\varepsilon_{i,t-j}/\sigma_{i,t-j}$ is negative, the effect of a shock on the log of the conditional variance is $\sum_{j=1}^{m}\beta_j - \sum_{k=1}^{n}\gamma_k$. In order to get a strictly stationary EGARCH, it is necessary that $\left|\sum_{j=1}^{l}\alpha_j\right| < 1$. See He, Terasvirta and Malmsten (2002) and Karanasos and Kim (2003) for details about stationarity conditions in E-GARCH and ARMA-E-GARCH models.

An alternative to the E-GARCH models is the GJR model, in which the impacts of $\varepsilon_{i,t-j}^2$ on the variance is different when $\varepsilon_{i,t-j}$ is positive or negative. These different effects on the conditional variance are dealt with in Glosten, Jaganathan and Runkle (1993), GJR, because they find a negative relationship between the expected conditional monthly return and the expected monthly conditional variance of the returns in the stock markets. They employ a modified GARCH-M to allow that positive and negative innovations have different impacts on the conditional variance. The GJR model parts from a standard GARCH and includes an additional term for the lagged negative residuals.

[2] See Lobo (2000) and Rabemananjara and Zakoian (1993) for more details.

Consider the following GJR(1,1) model:

$$h_{i,t} = \omega + \alpha\varepsilon_{i,t-1}^2 + \beta h_{i,t-1} + \delta N_{i,t-1}\varepsilon_{i,t-1}^2 \quad (7)$$

where $N_{i,t-1}$ is a dummy variable that assumes a value of 1 if $\varepsilon_{i,t-1}^2 < 0$ and zero otherwise. If $\delta > 0$, than $h_{i,t}$ will be bigger for a negative shock in comparison to a positive shock of the same magnitude. So, if $\varepsilon_{i,t-1} \geq 0$ the effect of a shock on the conditional variance is $\alpha\varepsilon_{i,t-1}^2$, with the dummy assuming the value of zero. When $\varepsilon_{i,t-1} < 0$, $N_{i,t-1}$ = 1, the effect of a shock will be $(\alpha + \delta)\varepsilon_{i,t-1}^2$.

2.3. Multivariate GARCH models

There is a large list of models derived from the univariate ARCH/GARCH family, like the ARCH-M, I-GARCH, TARCH, and E-GARCH. It is possible expand them to the multivariate form, which can be classified into three groups: i) a generalized form of the univariate GARCH; ii) linear combinations and; iii) linear combinations of univariate GARCH.

The first group can be divided into the VEC models (whose Vech(.) operator stacks an inferior triangular matrix like a vector), the BEKK (acronym for the multivariate models summarized in Baba, Engle, Kraft and Kroner), and factor models. In the second group are orthogonal models and hidden factor models. In the last category are the models with dynamic and constant conditional correlation, the dynamic general covariance model, and Copula-Garch.

2.3.1. The BEKK model

In the class of the multivarite GARCH models, the VEC and BEKK models are largely employed in the analysis of co-movements in the conditional variance and covariance of time series. With the proper parametering it is possible to derive one from the other, as shown in Engle and Kroner (1995). The problem of these models is the number of parameters to be estimated and makes employing it in estimations with more than two assets difficult. To avoid this problem a diagonal model can be employed, in which it is assumed that the matrixes A and G are diagonal and each element of $h_{ij,t}$ depends only of its own lags and the values of $\varepsilon_{it}\varepsilon_{jt}$; Consider the following BEKK(1,1,K), in which K=1:

$$\mathbf{H}_t = \mathbf{C}^{*'}\mathbf{C}^* + \sum_{k=1}^{K}\mathbf{A}_k^{*'}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'}\mathbf{A}_k^* + \sum_{k=1}^{K}\mathbf{G}_k^{*'}\mathbf{H}_{t-1}\mathbf{G}_k^* \quad (8)$$

Where $\mathbf{C}^*, \mathbf{A}_k^*$, and $\mathbf{G}_k^*$ are $N \times N$ parameter matrixes and $\mathbf{C}^*$ is a triangular superior matrix. The difference in the VEC model is that the parameters of the BEKK are not directly the impact of the different lagged terms in $\mathbf{H}_t$. Under certain conditions (8) will be positive and defined, as can be seen in Engle and Kroner (1995).

The number of parameters in the BEKK(1,1,1) model is $N(5N+1)/2$. A way to lower the number of estimated parameters is to get the matrixes $\mathbf{A}_k^*$ and $\mathbf{G}_k^*$ diagonal. This model is known as the diagonal BEKK and can be employed to explain the causality relationships between assets' variance and covariance.

To test the presence of asymmetry in response to shocks in the conditional variance and covariance, we employ the following modified BEKK:

$$\mathbf{H}_t = \mathbf{C}^{*'}\mathbf{C}^{*} + \mathbf{A}_k^{*'}\boldsymbol{\varepsilon}_{t-1}\boldsymbol{\varepsilon}_{t-1}^{'}\mathbf{A}_k^{*} + \mathbf{D}\left[\boldsymbol{\varepsilon}_{t-1}\left(\boldsymbol{\varepsilon}_{t-1} < 0\right)\right]\left[\boldsymbol{\varepsilon}_{t-1}\left(\boldsymbol{\varepsilon}_{t-1} < 0\right)\right]^{'} \\ \mathbf{D}\left[\boldsymbol{\varepsilon}_{t-1}\left(\boldsymbol{\varepsilon}_{t-1} < 0\right)\right]\left[\boldsymbol{\varepsilon}_{t-1}\left(\boldsymbol{\varepsilon}_{t-1} < 0\right)\right]^{'}\mathbf{D} + \mathbf{G}_k^{*'}\mathbf{H}_{t-1}\mathbf{G}_k^{*} \qquad (9)$$

where $\mathbf{C}^{*}, \mathbf{A}_k^{*}$, $\mathbf{G}_k^{*}$, and D are parameter matrixes; $\mathbf{C}^{*}$ is an undefined matrix; and $\mathbf{A}_k^{*}$, $\mathbf{G}_k^{*}$, and D are diagonal matrixes. The asymmetric terms appear at the parameter matrix D.

3. Interdependence of the conditional variance between Latin American stock markets

In this section we attempt to investigate the structure of the interdependence between the most important emerging Latin American stock markets, finding the causality of the variance and including the international stock market.

3.1. Data and results from the E-GARCH model

The sample is composed of daily return data from the Argentinean (Merval), Brazilian (Ibovespa), and Mexican (IPC) markets with the Dow Jones as a proxy of the international market, ranging from July 3rd, 1997 to December 29th, 2006. The Dow Jones index is included as suggested in Phylaktis and Ravazzolo (2005), to avoid an incomplete analysis. Anakiramanan and Lamba (1998) and Kearney (2000) also discuss the importance of the influence of the US market on other stock markets. Graph 1 shows the data. It can bee seen in the graphs that volatility clusters are common to the countries and the clustering is stronger or weaker between them, in response to shocks originated by endogenous and exogenous to the markets, like in the 1990s crisis.

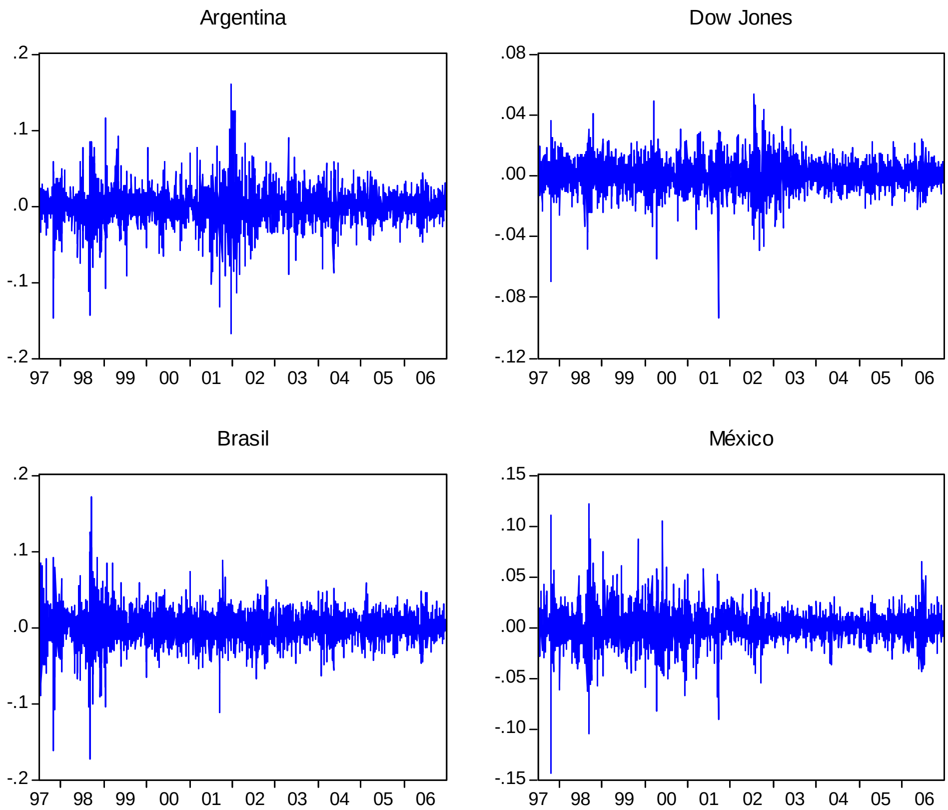


Figure 1 – Market returns - July 3rd, 1997 to December 29th, 2006

The results of the E-GARCH estimations are shown in Table 1. It can be observed that in the sample period, the Brazilian market has the least response to positive shocks on the conditional variance. A positive shock has an effect of 0.1995 + (-0.1237) = 0.0758 on the log of the conditional variance. For a negative shock the impact is 0.1995 – (-0.1237) = 0.3233. Argentina has the biggest responses to positive shocks 0.2336 + (-0.0689) = 0.1647, while for a negative shock the effect is 0.2336 – (-0.0689) = 0.3024.

The biggest negative response to a negative shock is observed in Mexico, 0.2290 – (-0.1354) = 0.3644, and the response to a negative shock is of 0.2290 + (-0.1354) = 0.0936. This result for Mexico does not account for the effects of the Mexican crises at the end of 1994.

The persistence in the conditional variance is the biggest in Argentina, 0.9643, and is 0.9570 and 0.9493 in México and Brazil, respectively. This shows that Mexico is more sensitive to negative shocks on the conditional variance, but does not have the highest persistence in comparison to the other two Latin American markets. The Brazilian market shows the least persistence on the conditional variance and at the same time the least response to negative shocks.

Table 1 – Results of the E-GARCH estimation - July 3rd, 1997 to December 29th, 2006.

Parameters	Argentina	Brazil	Mexico	Dow Jones
Mean Equation				
μ	0.0395	0.0313	0.0588	0.0248

	(0.0173)**	(0.0199)	(0.0187)*	(0.0198)
Variance equation				
ω	-0.4509 (0.0630)*	-0.5550 (0.0702)*	-0.5419 (0.0653)*	-0.1892 (0.0285)*
$\ln\left(\sigma_{i,t-j}^2\right)$	0.9643 (0.0072)*	0.9493 (0.0081)*	0.9570 (0.0067)*	0.9854 (0.0027)*
$\left\|\frac{\varepsilon_{i,t-j}}{\sigma_{i,t-j}}\right\|$	0.2336 (0.0231)*	0.1995 (0.0217)*	0.2290 (0.0252)*	0.0663 (0.0136)*
$\frac{\varepsilon_{i,t-k}}{\sigma_{i,t-k}}$	-0.0689 (0.0142)*	-0.1237 (0.0153)*	-0.1354 (0.0167)*	-0.1058 (0.0093)*
R-squared	0.0001	0.0001	0.0010	0.0006
S,E, of regression	0.0243	0.0231	0.0170	0.0106
Sum squared residual	1.4548	1.3227	0.7117	0.2776
Durbin-Watson stat	2.0075	2.0050	2.0388	2.0437
Mean dependent var	0.0004	0.0004	0.0007	0.0002
S,D, dependent var	0.0242	0.0231	0.0170	0.0106

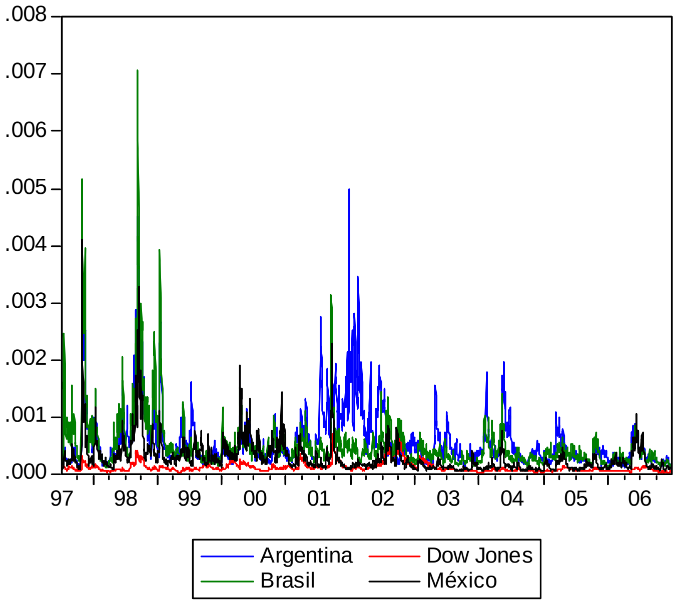
Mean equation $y_{i,t} = \mu_{i,t} + \varepsilon_{i,t}$, with $\mu_{i,t} = \delta h_{i,t}$. In parenthesis are the standard deviations. *, **, and *** stand for statistically significant at the 1%, 5%, and 10% levels.

During the last decade Latin American markets were strongly affected by economic reforms and internal and external shocks. The results show that in the US market a positive shock diminishes the conditional variance in 0.0395 and the response is quite lower to a negative shock in comparison to the emerging markets. The persistence is higher in the US market than in Latin American markets.

The estimated coefficients for the mean equation show that the risk premium changes over time for these markets, ranging from 0.0248 to 0,0588. For Brazil and Dow Jones the coefficient is not statistically significant.

3.2. Causality in the conditional variance in a regional structure

Stock markets with different sizes, structures, and Geographic location can show a high degree of co-movements after a shock in one of the markets. If markets are quite different, this co-movement suggests the existence of a mechanism that transmits internal shocks to international markets (FORBES and RIGOBON, 2002), and the precedence in time can be tested by Granger causality tests (Granger, 1969). Lags used in this test are defined with the help of a VAR (Vector Auto Regression) by the Schwarz criteria and the least sum of squared residuals, due to the high sensitivity of the results of the causality tests on the chosen lag. Causalities were also estimated with arbitrary chosen lags of five and ten periods, to check for the consistency of the results. Graph 2 shows the series of conditional variance generated from the E-GARCH formerly estimated.



Graph 2 – Latin American series of conditional variance – July,1997 to December, 2006.

The conditional variance of the returns of the Latin American markets shows a similar path. Higher and lower conditional variance periods are well defined. In 1997, 1998, the beginning of 1999 and 2001, the periods of crisis in Asia, Russia, Brazil, and Argentina, there is high volatility. Furthermore, the US market is less volatile than the Latin American, as expected. The conditional variance is the highest in Brazil up to the middle of 2001, and since then the highest volatility occurs in Argentina. Series move in the same direction, which may be due to relationships between the markets.

Table 2 shows the results for the Granger causality tests for the series of conditional variance generated by the E-GARCH estimation. There is no precedence in the Granger sense between the US and Latin American markets. The conditional variance of the Brazilian market causes the Argentinean and Mexican, which means that the Brazilian market transmits volatility to the others.

Table 2 – Granger causality tests results – July, 1997 to December, 2006.

Null hypothesis	Lags	Obs	F statistic	F Prob.
$h_{DowJones,t}$ does not Granger cause $h_{Argentina,t}$	1	2476	1.8746	0.1711
$h_{Argentina,t}$ does not Granger cause $h_{DowJones,t}$	1	2476	0.5336	0.4652
$h_{Brasil,t}$ does not Granger cause $h_{Argentina,t}$	**2**	**2475**	**18.5742**	**0.0000**
$h_{Argentina,t}$ does not Granger cause $h_{Brasil,t}$	2	2475	0.3503	0.7045
$h_{México,t}$ does not Granger cause $h_{Argentina,t}$	1	2476	1.8086	0.1788
$h_{Argentina,t}$ does not Granger cause $h_{México,t}$	1	2476	0.9367	0.3332
$h_{Brasil,t}$ does not Granger cause $h_{DowJones,t}$	1	2476	0.8938	0.3446
$h_{DowJones,t}$ does not Granger cause $h_{Brasil,t}$	1	2476	1.2824	0.2576

$h_{México,t}$ does not Granger cause $h_{DowJones,t}$	1	2476	1.8373	0.1754
$h_{DowJones,t}$ does not Granger cause $h_{México,t}$	1	2476	0.1036	0.7476
$h_{México,t}$ does not Granger cause $h_{Brasil,t}$	1	2476	0,0002	0,9884
$h_{Brasil,t}$ does not Granger cause $h_{México,t}$	**1**	**2476**	**38.2098**	**0.0000**

When the five and ten lags are employed, the results of the tests with shorter lags are confirmed and some other significant causalities also arise (Table 3). These results mean that more conditional variance is transmitted when larger periods are considered. The regional leading behavior of the Brazilian market is confirmed. A relationship between the conditional variances of the US and the Latin American markets also arises, especially with the Brazilian. Persistence and linkages between the conditional volatility of the markets are confirmed. This happens because of the test's sensitivity to the lag choice.

These regional links between markets are due to the economic relationships of the economies and likely evaluations of them by market agents. The trade relationships forecast stock returns and country vulnerability as a consequence (Forbes e Rigobon 2002). The results show the relationships between market conditional variance, and so the international stock market has to be considered.

Table 3 - Granger causality tests results for Latin Amecica – July, 1997 to December, 2006.

Null hypothesis	Lags	Obs	F statistic	F Prob.
$h_{DowJones,t}$ does not Granger cause $h_{Argentina,t}$	5	2472	1.0467	0.3883
$h_{Argentina,t}$ does not Granger cause $h_{DowJones,t}$	**5**	**2472**	**4.2984**	**0.0007**
$h_{DowJones,t}$ does not Granger cause $h_{Argentina,t}$	10	2467	1.6572	0.0851
$h_{Argentina,t}$ does not Granger cause $h_{DowJones,t}$	**10**	**2467**	**3.3874**	**0.0002**
$h_{Brasil,t}$ does not Granger cause $h_{Argentina,t}$	**5**	**2472**	**9.0952**	**0.0000**
$h_{Argentina,t}$ does not Granger cause $h_{Brasil,t}$	5	2472	1.6002	0.1566
$h_{Brasil,t}$ does not Granger cause $h_{Argentina,t}$	**10**	**2467**	**9.0876**	**0.0000**
$h_{Argentina,t}$ does not Granger cause $h_{Brasil,t}$	10	2467	0.9885	0.4510
$h_{México,t}$ does not Granger cause $h_{Argentina,t}$	**5**	**2472**	**2.6766**	**0.0203**
$h_{Argentina,t}$ does not Granger cause $h_{México,t}$	**5**	**2472**	**2.7440**	**0.0177**
$h_{México,t}$ does not Granger cause $h_{Argentina,t}$	10	2467	1.7210	0.0705
$h_{Argentina,t}$ does not Granger cause $h_{México,t}$	**10**	**2467**	**2.6661**	**0.0031**
$h_{Brasil,t}$ does not Granger cause $h_{DowJones,t}$	5	2472	0.7425	0.5916
$h_{DowJones,t}$ does not Granger cause $h_{Brasil,t}$	**5**	**2472**	**4.6531**	**0.0003**
$h_{Brasil,t}$ does not Granger cause $h_{DowJones,t}$	**10**	**2467**	**2.7985**	**0.0019**
$h_{DowJones,t}$ does not Granger cause $h_{Brasil,t}$	**10**	**2467**	**4.2128**	**0.0000**
$h_{México,t}$ does not Granger cause $h_{DowJones,t}$	**5**	**2472**	**2.6330**	**0.0221**
$h_{DowJones,t}$ does not Granger cause $h_{México,t}$	5	2472	1.2071	0.3032
$h_{México,t}$ does not Granger cause $h_{DowJones,t}$	10	2467	1.6682	0.0824
$h_{DowJones,t}$ does not Granger cause $h_{México,t}$	10	2467	1.1645	0.3101

$h_{México,t}$ **does not Granger cause** $h_{Brasil,t}$	**5**	**2472**	**8.9720**	**0.0000**
$h_{Brasil,t}$ **does not Granger cause** $h_{México,t}$	**5**	**2472**	**11.6952**	**0.0000**
$h_{México,t}$ **does not Granger cause** $h_{Brasil,t}$	**10**	**2467**	**6.9789**	**0.0000**
$h_{Brasil,t}$ **does not Granger cause** $h_{México,t}$	**10**	**2467**	**7.0315**	**0.0000**

3.3. Multivariate models

It is common to see a high degree of persistence in the conditional variance series of the returns of financial assets when univariate models are employed. Sometimes the persistence is not observed when the series are linearly linked. This has a strong implication for the long run forecasting of variance and conditional variance of assets. In this section a BEKK(1,1,1,) model is employed for comparison with the univariate models. The model is estimated with and without asymmetry. The relationships between countries are estimated pairwise and in groups of three, with the third being the international market.

Given the importance of the shocks in the mean equation, the specification of the model was given great attention, beginning with a VAR with eight lags and choosing the best by the Schwarz criteria (GOEIJ and MARQUERING, 2004). Results of the pairwise estimation (for the conditional variance only) are shown in Table 4, which also shows a diagonal BEKK model with an asymmetry term in order to test for the difference between the influence of positive and negative shocks on the conditional covariance between the markets.

Table 4 – Estimation results of the BEKK models- July, 1997 to December, 2006.

Independent variabels	Argentina X Brazil		Argentina X México		Brazil X México	
	Diagonal BEKK	Diagonal asymmetric BEKK	Diagonal BEKK	Diagonal asymmetric BEKK	Diagonal BEKK	Diagonal asymmetric BEKK
Constant (1,1)	2.9E-10 (1.3E-11)*	3.3E-10 (1.6E-11)*	2.7E-10 (1.0E-11)*	3.4E-10 (1.7E-11)*	9.5E-11 (4.7E-12)*	1.0E-10 (5.4E-12)*
Constant (1,2)	1.9E-10 (1.1E-11)*	2.7E-10 (1.9E-11)*	8.6E-11 (6.2E-12)*	1.2E-10 (6.0E-12)*	9.5E-11 (6.0E-12)*	1.4E-10 (7.2E-12)*
Constant (2,2)	2.5E-10 (1.1E-11)*	6.5E-10 (2.7E-11)*	1.0E-10 (5.1E-12)*	1.2E-10 (4.9E-12)*	2.3E-10 (8.3E-12)*	4.5E-10 (1.7E-11)*
$\varepsilon^2_{1,t-1}$	0.6667 (0.0069)*	0.6921 (0.0075)*	0.5589 (0.0056)*	0.6188 (0.0097)*	0.8348 (0.0086)*	0.9109 (0.0095)*
$\varepsilon^2_{2,t-1}$	0.3710 (0.0031)*	0.4848 (0.0057)*	0.8966 (0.0095)*	0.6636 (0.0057)*	0.3128 (0.0031)*	0.3452 (0.0040)*
$\varepsilon^2_{1,t-1}\left(\varepsilon_{1,t-1} < 0\right)$		0.0033 (3.4592)		0.6766 (0.0296)*		-0.0122 (1.0686)
$\varepsilon^2_{2,t-1}\left(\varepsilon_{2,t-1} < 0\right)$		0.0101 (1.9363)		-0.2798 (0.0331)*		-0.0371 (0.3964)
$H_{1,t-1}$	0.8715 (0.0022)*	0.8671 (0.0028)*	0.9026 (0.0015)*	0.8551 (0.0043)*	0.8271 (0.0031)*	0.8094 (0.0035)*
$H_{2,t-1}$	0.9414 (0.0007)*	0.8932 (0.0035)*	0.8155 (0.0030)*	0.8561 (0.0026)*	0.9496 (0.0005)*	0.9306 (0.0021)*

Standard deviations in parentheses. Results of the mean equation were omitted (employing a VAR, a model with two lags for Argentina and Brazil, one for Brazil and Mexico and three for Brazil and Mexico was chosen). *, **, and *** stand for statistically significant at the 1%, 5%, and 10% levels.

All the coefficients are statistically significant in the diagonal BEKK model, which means that a multivariate model better explains the common behavior of the conditional variance of the returns than the univariate. On the other hand, asymmetric responses to shocks are not statistically significant between Argentina and Brazil and between Mexico and Brazil. The asymmetry coefficient for negative shocks is negative for Mexico in the equation with Argentina.

Results including the international market by means of the Dow Jones index are shown in Table 5. All the coefficients of the diagonal BEKK model are statistically significant. When asymmetry is included, the coefficients for asymmetry for Brazil in the model that includes Argentina and Dow Jones and for the Dow Jones in the model that includes Argentina and Mexico and Mexico and Brazil are not statistically significant. The sign of the coefficients of asymmetry has changed; Mexico now has a positive coefficient while Brazil and Argentina in the equation with Argentina, Dow Jones, and Brazil are negative. Argentina also has a negative coefficient in the equation with Dow Jones and Mexico.

In terms of causal relationships the significance of the estimated coefficients indicates bicausal relationships between the variance of the markets, confirming results of the bivariate tests.

Table 5 – Estimation Results of the BEKK models including international market – July, 1997 to December, 2006.

Independent variables	Argentina X Dow Jones X Brazil		Argentina X Dow Jones X México		México X Brazil X Dow Jones	
	Diagonal BEKK	Diagonal asymmetric BEKK	Diagonal BEKK	Diagonal asymmetric BEKK	Diagonal BEKK	Diagonal asymmetric BEKK
Constant (1,1)	3.2E-10 (1.3E-11)*	2.7E-10 (1.2E-11)*	2.9E-10 (1.1E-11)*	3.6E-10 (1.7E-11)*	5.2E-10 (8.3E-12)*	3.4E-10 (1.1E-11)*
Constant (1,2)	1.2E-11 (1.4E-12)*	1.6E-11 (1.6E-12)*	1.1E-11 (1.6E-12)*	1.7E-11 (2.3E-12)*	2.0E-10 (1.2E-11)*	2.1E-10 (1.1E-11)*
Constant (1,3)	1.8E-10 (1.2E-11)*	2.1E-10 (1.4E-11)*	9.0E-11 (7.2E-12)*	1.3E-10 (8.2E-12)*	2.1E-11 (1.7E-12)*	1.2E-11 (1.5E-12)*
Constant (2,2)	1.3E-12 (2.5E-13)*	1.8E-12 (3.1E-13)*	1.9E-12 (2.4E-13)*	2.0E-12 (2.3E-13)*	1.3E-09 (4.7E-11)*	1.2E-09 (4.7E-11)*
Constant (2,3)	1.0E-11 (1.4E-12)*	1.8E-11 (2.1E-12)*	1.0E-11 (8.5E-13)*	1.1E-11 (9.1E-13)*	2.8E-11 (2.5E-12)*	3.2E-11 (2.6E-12)*
Constant (3,3)	2.6E-10 (1.2E-11)*	5.0E-10 (2.2E-11)*	1.2E-10 (4.6E-12)*	1.3E-10 (5.2E-12)*	3.8E-12 (3.2E-13)*	1.9E-12 (2.5E-13)*
$\varepsilon^2_{1,t-1}$	0.5911 (0.0067)*	0.5283 (0.0071)*	0.5514 (0.0062)*	0.5651 (0.0090)*	0.5098 (0.0039)*	0.4965 (0.0041)*
$\varepsilon^2_{2,t-1}$	0.4404 (0.0044)*	0.4159 (0.0046)*	0.4097 (0.0041)*	0.3819 (0.0045)*	0.5402 (0.0103)*	0.4525 (0.0076)*
$\varepsilon^2_{3,t-1}$	0.3726 (0.0036)*	0.4177 (0.0049)*	0.8275 (0.0111)*	0.7788 (0.0092)*	0.3553 (0.0032)*	0.3958 (0.0040)*
$\varepsilon^2_{1,t-1}\left(\varepsilon_{1,t-1}<0\right)$		-0.2713 (0.0480)*		-0.7211 (0.0381)*		0.2719 (0.0315)*
$\varepsilon^2_{2,t-1}\left(\varepsilon_{2,t-1}<0\right)$		0.2070 (0.0463)*		0.0207 (0.0500)		-0.2396 (0.0285)*
$\varepsilon^2_{3,t-1}\left(\varepsilon_{3,t-1}<0\right)$		-0.0580 (0.0457)		0.1370 (0.0373)*		0.0439 (0.0424)
$H_{1,t-1}$	0.8936 (0.0023)*	0.9068 (0.0022)*	0.9055 (0.0016)*	0.8677 (0.0047)*	0.8321 (0.0018)*	0.8545 (0.0038)*
$H_{2,t-1}$	0.9372 (0.0011)*	0.9335 (0.0020)*	0.9414 (0.0011)*	0.9448 (0.0012)*	0.8383 (0.0049)*	0.8603 (0.0052)*
$H_{3,t-1}$	0.9411 (0.0007)*	0.9159 (0.0019)*	0.8437 (0.0028)*	0.8430 (0.0028)*	0.9360 (0.0012)*	0.9399 (0.0015)*

Standard deviations in parentheses. Results for the mean equation are omitted (employng a VAR, one lag for all the relationships was chosen). *, **, and *** stand for statistically significant at the 1%, 5%, and 10% levels.

The selection criteria indicate that the best model is the one that includes asymmetry, except for the model that includes Argentina, Dow Jones, and Brazil. The inclusion of the international stock market and of asymmetry coefficients leads to more robust results, which allows for a more precise analysis of the relationsships between financial markets through conditional variance and covariance, pointing to a joint movement between the markets.

It is likely that in emerging markets the information dissemination is asymmetric. In the beginning only well-informed traders take a position. The transmission of the information between traders leads to the taking of positions also by the less-informed traders. After some intermediate equilibriums, a final equilibrium with less volatility is achieved. Furthermore, equilibrium prices do not reflect all the private information on which the investors rely their transactions, there is also noise in the process. As the noise differs in size between developed and emerging markets, equilibrium prices will also differ, reflecting private information. Noise is bigger in emerging markets, and so will be the relationship between volume traded and the volatility (Girard and Biswas, 2007).

As assets move together, shocks in the same direction mean a greater risk than shocks in opposite directions. The risk of investing in two assets that have a high positive correlation is higher than investing in two less correlated assets (Goeij e Marquering, 2004). The pattern of the co-movements can reflect the degree of economic integration between countries or trade areas, as described in Eun and Shim (1989) and Koch and Koch (1991).

4. Conclusion

This paper aimed to identify the relationships between the conditional variance and its co-movements in Latin American markets. It employed univariate E-GARCH and multivariate GARCH (BEKK) models. The risk-return relationsships are quite near for Brazil and Argentina. For Brazil the coefficient is not statistically significant at the 10% level, which also occurs in the case of the Dow Jones. For Mexico the coefficient is small, but significant at the 1% level.

Argentina exhibits the highest response to positive shocks on the conditional variance, the smallest response to negative shocks, and the highest persistence of the conditional variance between the analyzed Latin American countries. Brazil has the smallest response to positive shocks and the smallest persistence in the conditional variance, while Mexico has the highest response to negative shocks. The Dow Jones has a negative response to positive shocks, which suggests a reduction of the market volatility in case of good news, but the response to positive shocks is the half of the Latin Americans markets. The Dow Jones also shows the highest persistence in the conditional variance between the analyzed markets.

The relationships between the markets' conditional variance tested by means of the Granger causality test shows that conditional variance in the Brazilian market is transmitted to the other Latin American markets when the optimal lag choice is employed. Employing arbitrary lags of five and ten periods, this relationship is confirmed and the importance of the US market also shows up.

The BEKK models results point to the existence of a co-movement between Latin American markets and with the international market. The importance of the US market confirms the former results in the literature. All the coefficients are statistically significant in the bivariate and trivariate models without asymmetry. Asymmetry is not significant in the bivariate models for Brazil and Argentina and Brazil and Mexico. In the model that includes the Dow Jones there is no statistical significance for the Dow Jones' asymmetry in the models for Argentina and Mexico and Brazil and Mexico. The asymmetry coefficient is not

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statistically significant for Brazil in the model that includes Brazil, Argentina, and Dow Jones. The

The results indicate that there is a relationship between the conditional variance of Latin American markets as well as between these and international markets during the period analyzed, which is of interest for decision-making in economic policy and resource allocation. The same fundamentals of these economies or a similar evaluation of the regional markets by foreign investor are important for the behavior of the markets.

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