Submission paper

"Latin American stock markets' volatility spillovers during the financial crises: a multivariate FIAPARCH-DCC framework"

by

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3rd EMG Conference on Emerging Markets Finance

5-6 May 2011
Emerging Markets Group, Faculty of Finance,
Cass Business School, City of London
Cass Business School
106 Bunhill Row
London EC1Y 8TZ UK

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Abstract: The main purpose of this paper is to analyze the volatility spillovers in Latin American emerging stock markets. A multivariate Fractionally Integrated Asymmetric Power ARCH model with dynamic conditional correlations of Engle (1982) (DCC-E) (M-FIAPARCH-DCCE) with a Student-t distribution is employed. The underlying idea is to detect eventual volatility spillovers in either in mean returns or conditional variance. We (examine) whether considering for long-memory and asymmetry in emerging stock markets behavior may provide more insights into the volatility spillovers phenomenon. In this paper we select daily frequency stock indexes covering four emerging countries in Latin America for the period (January, 1995- September, 2009). Our results point out the importance of volatility spillovers in these countries. Moreover, long-memory and asymmetry in emerging stock market dynamics seem to provide more insights into the transmission of volatility shocks. More interestingly, the analysis of the DCCEs behavior over time via multivariate cointegration, VECM and the Cholesky variance decomposition shows shifts behavior around major LA financial crisis and recent subprime crisis. On the practical side, these results may be useful for international portfolio managers and LA stock market authorities.

1. Introduction

The empirical works concerned with the volatility spillovers between stock markets are extremely abundant. Evidently, understanding such dynamic relationship between stock markets is a crucial question for academicians, investors and international portfolio managers. For academicians, it is not surprising because such dynamic linkage between stock markets may provide more ideas about the informational efficiency of local stock markets. It may offer more insights into the volatility shocks transmission between stock markets and how quickly the news is transmitted across markets. For international portfolio managers, it is necessary to understand the dynamic linkage between stock markets in order to evaluate the stock market risk and to construct the appropriate hedging strategy. In the empirical literature, it is well documented that stock markets returns exhibit some major stylized facts: (1) *Volatility clustering:* There are periods of high and low volatility. The high absolute returns tend to be followed by high absolute returns and small absolute returns tend to be followed by small absolute returns; (2) *Leptokurtosis effect:* the stock market return's distribution exhibits departure from the Gaussian distribution. They present much fatter tails than the normal distribution assumes (i.e. the probability of extreme returns is much larger), (3) *Leverage effect:* The volatility tends to be larger for the price falls than for price increases when the magnitude of the price increase and fall are the same. This is asymmetric influence of negative and positive information on future level of volatility; (4) *Skewness:* The returns distribution exhibits some degree of skewness, (5) Autocorrelation of rates of returns especially in periods of low variability and (6) *Long memory:* for stock markets, it is commonly admitted that high order autocorrelation coefficients of squared returns (errors) are statistically significant (see, e.g. Ding et al., 1993 and Ding and Granger, 1996).

Earlier studies including Hamao *et al.* (1990), King and Wadhwani (1990) and Schwert (1990) were concerned with major developed stock markets and focused on both the first and the second moments of the stock return distributions. However, during the last two decades, the empirical researches were concentrated on emerging stock markets. In fact, the research issue inherent to volatility spillovers between emerging stock markets has been significantly enhanced by the economic growth in some emerging countries in the increasing openness in their capital markets. More interestingly, the recent financial crises have shown the speed and the virulence of the volatility spillovers between either major stock markets or emerging markets. On the other side, previous studies were focused on both the first and the second moments of the stock return distributions. However, recent empirical studies including Granger and Ding (1995), Ding *et al.* (1993) have shown that although stock market returns exhibit little serial correlation, the absolute and squared stock returns and their power transformations are highly correlated over time. These authors have investigated the autocorrelation structure of daily stock returns in the context of major developed markets and revealed a strong positive autocorrelations for long lags. Induced by these results, they suggested the Asymmetric Power ARCH (APARCH)

model. Consequently, some other nested models are provided in the empirical literature. Therefore, Baillie *et al.* (1996) have proposed the Fractionally Integrated GARCH model (FIGARCH). Their main idea is to provide a model which is able to distinguish between short and long memory in the conditional variance.

Our study is founded on a multivariate framework to encompass several channels through which news and consequently volatility shocks are transmitted between emerging stock markets. In other words, an attractive research question is to see whether the multivariate long-memory GARCH-class models are appropriate to provide more insights into the volatility spillovers between emerging stock markets. In fact, it is well known that stock market volatilities are changing over time. So, if we consider for this volatility spillover over time within emerging stock markets, it would be interesting to analyze the volatility spillovers in a multivariate long-memory GARCH-class approach. Our investigation is focused on Latin American (henceforth, LA) emerging stock markets; namely Argentina, Brazil, Chile and Mexico. Our choice is motivated by the fact that they are considered as the most mature markets among the emerging markets in the region. Besides, over the past decade LA emerging markets authorities have engaged a vast program of financial liberalization. Subsequently, the capital flows in the region have risen rapidly since the international portfolio managers included emerging market securities in their portfolios in order to increase their potential diversification benefits.

In financial theory, the "contagion" phenomenon has been largely apprehended in the financial economic literature. However, there's no unanimous definition and no common measure for the 'contagion'. In the present work, we refer to Forbes and Rigobon (2001) to define "contagion". According to these authors, the 'contagion' is considered as 'a significant increase in cross-market linkages after a shock to an individual country (or group of countries)", (Forbes and Rigobon, 2001, p. 2). According to this definition, high degree of co-movement between two markets during both stability and crisis periods is not sufficient to identify "contagion". Some other authors including Edwards (2000), Gelos and Sahay (2000) assimilate "contagion" to volatility spillovers from one market to another that cannot be explained by macroeconomic or policy factors such as trade, capital flows and policy. In the present study, the stock market volatility shocks transmission across stock markets is considered. All the other classes of economic or policy spillovers are deliberately passed over in this research.

On the practical level, the research question dealing with volatility spillovers between LA stock markets was largely investigated in the literature (see, among others, Chen *et al.*, 2002; Johnson and Soenen, 2003; Fujii, 2005; Arouri *et al.* 2008, and Bora *et al.* 2009) and many interactive linkages have been founded. However, all prior studies were based on standard empirical approaches including cross-correlation's function analysis, multivariate cointegration, VAR models, regime switching models, stochastic volatility models, univariate and multivariate GARCH models (henceforth, MGARCH). We should mention that the MGARCH models were initially in the 1980s and the first half of the 1990s. Since the 1990s, the multivariate approach has experienced a very extensive improvement (See, Franses and van Dijk, 2000 and Gourièroux, 1997 for a survey). We presume that a multivariate approach can provide more imminent conclusions for portfolio managers in hedging stock market risk and asset allocation's decisions than can be obtained when using separate univariate models. Thus, the multivariate approach seems to be able to generate more relevant outcomes regarding the dynamic adjustments of the conditional variances of various emerging stock market indexes time series. Emerging stock market (co)volatilities can be apprehended within a multivariate long-memory ARCH/GARCH-class framework.

More specifically, we investigate whether multivariate models can outperform their univariate counterparts. In this paper, we employed multivariate FIAPARCH (henceforth, MFIAPARCH) models in order to examine the volatility transmission mechanism between emerging stock markets. Our study is distinguishable from previous empirical studies in at least two points. First of all, the use of a multivariate long-memory GARCH-class, namely the AR-FIAPARCH models with Student-t distribution for the stock return innovations. In line with Conrad (2010), we believe that the FIAPARCH model is appropriate to consider for some major stylized facts in stock market volatility. Comparing to other long-memory GARCH-class models, the FIAPARCH model seems to be more flexible in the conditional variance specification. It allows for (1) the asymmetric reactions of volatility to positive and negative shocks, (2) the high degree of volatility persistence in the stock market dynamics (see, e.g. Ding et al., 1993 and Ding and Granger, 1996) and (3) the data to determine the power of returns for which the predictable structure in the volatility pattern is the strongest (Conrad et al., 2010, p. 2). Secondly, this empirical approach is implemented for recent data

sets covering the major emerging stock markets in the LA region. The selected sample period runs from January 1995 to September 2009 and includes some major volatility shocks in both developed and emerging stock markets. To the best of our knowledge this approach has never been applied in the context of the LA emerging stock markets.

The layout of the present paper is as follows. Section 2 reports a literature review relating MGARCH models and volatility spillovers. Section 3 presents the univariate and the MFIAPARCH (henceforth MFIAPARCH) models. Section 4 provides a preliminary analysis relative to the selected emerging stock market behavior. The empirical results are displayed and discussed in section 5, while section 6 reports the summary and some concluding remarks.

2. Stock market volatility spillover analysis with a multivariate GARCH-class models

It is well known that the main underlying idea of portfolio theory is related to the advantages derived from sector and geographic diversification. During the last two decades, international capital flows have spectacularly increased subsequent to rapid mutations in global financial markets such as technological innovations and financial markets liberalization (foreign exchange rate controls, abolishing of some several trading barriers). All these features have manifestly increased the degree of stock market integration and promoted empirical research dealing with the dynamic relationship and volatility spillovers between national emerging stock markets. Over the years a large number of empirical studies were devoted to the stock market interactive relationships and volatility spillovers. In this perspective, many econometric methodologies were employed. In this section, we expose an empirical literature review focused on the employ of the MGARCH-class models. The initial empirical studies concerned with volatility spillovers between stock markets are focused on larger sets of developed countries. The major studies were concerned with stock market behavior during the period of the US stock market crash (October 1987). In this context, some researchers including Hamao *et al.* (1990), King and Wadhani (1990) and Schwert (1990) analyzed the stock market dynamics during the pre- and post-crash periods. Using high frequency data, Susmel and Engle (1990), provided evidence of asymmetry in the volatility spillovers between major developed stock markets. Similar results were given by Koutomos and Booth (1995) and Bae and Karolyi (1994). They revealed that stock markets have different reactions to positive and negative volatility shocks. In other research, Lin *et al.* (1994) proved that volatility spillovers may be different for global and local shocks. Theodossiou and Lee (1993) studied the relationship between some major stock markets using a MGARCH-in-mean model. Their results confirm the presence of mean and volatility spillovers between some of these markets. Similar findings were given by Karolyi (1995). Using a bivariate GARCH model, the author analyzed the dynamic linkage between US and Canadian stock market returns and return volatilities. He concluded that volatility shocks are transmitted from the US to the Canadian stock market.

However, during the last two decades, a great number of empirical works were concerned with the volatility spillovers between emerging stock markets. The earlier studies were provided by Bekaert and Harvey (1995, 1997, and 2000) and Harvey and Ng (2006). The authors have examined the impact of a higher integration of global stock markets on emerging stock markets return, volatility and cross market correlations behavior over time. In their study, Caporale *et al.* (2000) have examined the volatility spillovers of some international stock markets and East Asian emerging markets during the 1997 financial crisis. Using a bivariate GARCH model with BEKK representation, the authors provided strong evidence of causality in variance between the selected markets. In their paper, Ledoit *et al.* (2003) employed a general diagonal-Vech formulation of the MGARCH model to estimate the volatility spillovers between seven major international stock markets. Compared to the traditional CCC and the diagonal BEKK models, the authors showed that this specification is more appropriate to consider for volatility spillovers between stock markets and value-at-risk estimations. A quite similar empirical approach was implemented by Lucey and Voronkova (2007) for the Russian stock market over the period 1995-2004. Their results failed to support the presence of long-run relationship between Russian stock market and other developed markets. Using a CCC-MGARCH specification, Worthington and Higgs (2004) examined the return and the volatility spillovers between some developed and emerging Asian stock markets. Their results reveal high correlation and volatility spillovers. Similar results were recently given by Sok-Gee *et al.* (2010). The authors employed an exponential GARCH (EGARCH) model to analyze interregional and intraregional spillovers effects in the ASEAN-5 stock markets.

Arouri *et al.* (2008) were concerned with the dynamic linkage between the main LA stock markets. The authors employed a multivariate DCC-GARCH model and the multivariate cointegration test to

analyze the conditional correlation behavior over time. Their findings revealed an increase in the short and the long term linkages between LA markets and the world market. In his paper, Hunter (2006) employed an asset-pricing model within a multivariate GARCH-in-Mean in the context of LA stock markets (Argentina, Chile and Mexico). He found that markets have not become integrated into the world equity market in the decade after liberalization. Also, Li and Majerowska (2008) used a multivariate asymmetric GARCH-BEKK model with DCC specification to examine the dynamic interactive relationship between two emerging markets (Warsaw and Budapest) and the German and US stock markets. They concluded that the two selected emerging markets are weakly linked to those in developed countries. Frank and Hesse (2009) estimated a DCC-MGARCH model in order to assess the dynamic linkage between advanced economies and emerging bond and stock markets during the recent financial crisis. The authors provided strong evidence of a sharp increase in the DCC behavior during the financial crisis period. Billio and Caporin's (2006) study is focused on the behavior over time of the DCC's MGARCH model using a two state Markov switching (MS) regime. The main purpose is to provide an alternative measure of the stock market contagion. Their results showed some discontinuities in the volatility spillovers behavior over time. In line with Billio and Caporin's (2006) paper, Diamantis (2009) was concerned with LA and the US stock market from January 1988 to July 2006. The author found that the short-term interdependence between LA and the US markets has been strengthened during the Asian financial crisis. Cho and Parhizgari (2008) examined structural breaks in the MGARCH's conditional correlation. According to these authors, a structural break measured by the shifts in mean and median of the DCC's behavior is considered as an alternative measure of stock market contagion. The obtained results support the presence of contagion effects for all the stock markets under research. In a more recent study Beirne *et al.* (2010) investigated the volatility spillovers between global and regional emerging stock markets. The authors have estimated a trivariate VAR GARCH model for 41 emerging stock markets and founded a strong evidence of volatility spillovers between regional and global stock markets. Bala and Premaratne (2010) analyzed the volatility spillovers between Singapore stock market and some major international markets using different models including a multivariate GJR-GARCH and Asymmetric MGARCH models. Using daily data covering the period 1992-2002, the authors provided evidence of a high degree of volatility co-movements between the selected markets. Also, Shamiri and Isa (2009) analyzed the volatility spillovers between US and the South East Asian stock markets (Singapore, Korea and Hong Kong) during the financial crisis period. They used a bivariate GARCH model with BEKK representation and found strong evidence of volatility spillovers running from the US market to all of the South East Asian stock markets. According to these authors, the degree of volatility persistence seems to change over time and across markets. Chiang *et al.* (2007) were concerned with the Asian financial crisis. Specifically, the authors researched eventual shifts in the MGARCH DCC's behavior for nine Asian stock markets over the period 1990-2003. They identified shifts in variance for the DCC's patterns during the crisis period (Chiang *et al.* 2007, p. 1206). Kaper and Lestano (2007) examined the interactive linkage among financial markets in Thailand and Indonesia. Analyzing the DCC behavior over time, they showed a certain degree of interdependence among countries which drops down during financial crises. Concerned with the Eastern European countries, Savva and Aslanidis (2009) investigated the degree of stock market integration using MGARCH model with smooth transition conditional correlation version (STCC). They found that the selected stock markets have increased their correlation to the euro-zone. Silvennoinen and Teräsvirta (2009) proposed a MGARCH model with a time-varying conditional correlation structure. The authors introduced a new double smooth transition conditional correlation (STDCC) GARCH model extending the STCC- GARCH model (see, Silvennoinen and Teräsvirta, 2005) by including another variable according to which the correlations change smoothly between states of constant correlations. The model is also implemented for some major international stock markets and provided evidence supporting increasing degree of integration in the capital markets. A similar empirical approach was adopted by Büttner and Bernd Hayo (2010) in order to analyze the conditional correlation interactions for six stock markets and foreign exchange markets from the euro area. They found that foreign exchange markets exhibit higher dynamic correlation than stock markets and the persistence effect is manifestly more important in foreign exchange markets. The DCC model is employed by Yu *et al.* (in press) in order to assess the development of stock market integration in Asian countries. Yu *et al.'s* (in press) findings provide evidence supporting changes in the integration processes.

In addition to these aforementioned studies, it should be stated that less attention is paid to the use of multivariate long-memory ARCH/GARCH-class models to analyze the volatility spillovers

between stock markets. However, a rich body of empirical researches was mainly involved in a univariate framework. Tessyière (1997), in a pioneer research has extended the univariate long-memory ARCH/GARCH models to the multivariate framework. The author suggested a bivariate FIGARCH model with CCC specification and revealed structural breaks in the long term structure of two major foreign exchange rate daily returns. Brunetti and Gilbert (1999) proposed a cointegrated bivariate FIAPARCH model to capture the co-volatility between two major crude oil markets (IPE and NYMEX). They found a common order fractional integration for the two volatility processes and they confirmed that they are fractionally cointegrated. Degiannakis (2004) and Niguez (2007) used univariate FIAPARCH specification to model the stock market dynamics. In particular, Degiannakis (2004) extended the standard ARCH model in order to capture the skewness and excess kurtosis in the stock return dynamics and the fractional integration of the conditional variance behavior. According to Degiannakis (2004), the FIAPARCH specification is appropriate to consider for both the fractional integration of the conditional variance as well as the skewed and leptokurtic conditional distribution of innovations. The author concluded that the FIAPARCH model with skewed Student-t distribution provides the most accurate one-day-ahead volatility forecasts. Dark (2004) has extended the univariate FIGARCH and FIAPARCH models to a bivariate framework. The author estimated a bivariate error correction FIGARCH and FIAPARCH models with constant conditional correlation (CCC) to research the causality linkage between all ordinary indexes and their SPI futures. Accordingly, this specification seems to be able to consider for some stylized facts such as long memory and asymmetries in volatility, and time varying correlations. A quite similar model was implemented by Kim *et al.* (2005) to explore the relationship between trading volume and stock market volatility.

Drawing together previous research, it can be found that the MFIAPARCH models are rarely employed to investigate the extent of volatility spillovers between emerging stock markets in a more detailed manner. Put it another way, some stylized facts such as long-memory and asymmetry in the conditional variance behavior are rarely taken into account in a multivariate framework. Only Conrad *et al.* (2003), Ho and Tsui (2004) and Conrad *et al.* (2010) estimated a MFIAPARCH specification to forecasting stock market volatility spillovers. Conrad *et al.* (2003) examined the ability of several long-memory ARCH-class models for ten major foreign exchange rates. They concluded that the FIAPARCH model is skilled to consider for asymmetry and long memory features. More interestingly, the authors provided evidence of superior forecasting ability compared to other nested ARCH/GARCH models. Ho and Tsui (2004) investigated the applicability of several multivariate GARCH-class models including multivariate APARCH, FIAPARCH, AGARCH, FIAGARCH models with CCC and DCC's of Engle (1982) specifications in order to consider for some stylized features such as long memory, asymmetric conditional volatility and time varying correlations for the case of four sectors of the Japanese stock market. The authors found that the fractionally integrated models outperform other GARCH-class models. In addition, they revealed that the conditional correlations are frequently highly positive and significantly time varying (Ho and Tsui, 2004, p. 19). In line with Ho and Tsui (2004), Conrad *et al.* (2010) examined the applicability of a multivariate constant conditional correlation version of the standard MFIAPARCH-CCC model with Bollerslev and Mikkelsen, 1996, and power ARCH specification of Ding, Granger and Engle, 1993 to forecast stock market volatilities for the G8 countries for the period January 1988- April 2004. The authors found that the fractional differencing parameter and the power transformation are quite similar across countries. Moreover, they concluded that this multivariate specification is generally appropriated for forecasting stock market volatility. More importantly, the out-of sample forecasting exercise revealed the ability of the M-FIAPARCH model. Our investigation is in line with Conard *et al.*'s (Ø) (2010). Specifically, we employed a M-FIAPARCH model with dynamic conditional correlation and Student-t error's distribution in order to identify volatility spillovers between LA stock markets. Also, we used a student-t distribution to consider the asymmetry in the emerging stock return's innovations. To the best of our knowledge, this is the first empirical study employing the MFIAPARCH with DCC specification to scrupulously understand the interactive linkages and volatility spillovers in the context of LA stock markets.

3. The univariate and MFIAPARCH models

3.1. The univariate FIAPARCH model

As it is widely recognized in the empirical literature, we presume that daily stock returns are governed by an AR(1) process.

$$(1-\zeta L)r_t = c + \varepsilon_t \tag{1}$$

with $\varepsilon_t = e_t\sqrt{h_t}$

In his paper, Tse (1998) has analyzed the conditional heteroscedasticity of foreign exchange rate using a FIAPARCH(1,d,1) model. Particularly, he has extended the Asymmetric Power ARCH model (APARCH) in order to consider for asymmetry and long memory features in the conditional variance behavior. Formally, the basic equation of a FIAPARCH(1,d,1) suggested by Tse (1998) can be expressed as (Tse, 1998, p. 51):

$$(1-\beta L)(h_t^{\delta/2}) = \left[(1-\beta L)-(1-\Phi)(1-L)^d\right](1+\gamma s_t)|\varepsilon_t|^{\delta} \tag{3}$$

Where $\omega \in (0,\infty), |\beta|<1, |\varphi|<1, 0 \le d \le 1, s_t = 1$ if $\varepsilon_t \le 0$ and 0 otherwise. According to Conrad *et al.* (2010) (in press), a sufficient condition for the conditional variance h_t to be positive for all t is that $\gamma > -1$ and the combination (φ, d, β) satisfies the inequality constraints provided by Conrad and Haag (2006)[1]. The leverage effect is measured by the coefficient γ, while δ is the power term parameter that takes finite positive values. When $\delta > 0$, negative shocks have more impact on volatility than positive shocks. One should note that when $d = 0$, the FIAPARCH(1,d,1) will be reduced to an APARCH(1,1) model which tests two major types of ARCH models[2] (Brooks *et al.*, 2000, p. 380). More precisely, if δ is equal to 1, the APARCH model nests Taylor's (1986)/Schwert's (1989) models. Conversely, if $\delta = 2$, it nests the Bollerslev's (1986) GARCH model. Furthermore, when $\gamma = 0$ and $\delta = 2$, the FIAPARCH (1,d,1) is reduced to a FIGARCH(1,d,1) model. This later includes in turn the Bollerslev's (1986) model when the fractional integration parameter is null. It should be pointed out that a very rich body of the empirical literature has shown that high frequency data including stock prices, foreign exchange rates, agricultural and energy commodity price dynamics are governed by integrated processes either in the mean or the variance processes. In contrast with the well documented I(1) process for the mean, there's no consensus for the truly integrated dynamics for the conditional variance. In their seminal paper, Baillie *et al.* (1986), stated that "For both the mean and the variance, being confined to only considering the extreme cases of I(0) and I(1) or stable GARCH and IGARCH processes, can be very misleading when long-memory, but eventual mean-reverting processes are generating the observed data" (Baillie *et al.*, 1996, p. 21). More interestingly, the authors stressed that time series displaying long-memory FIGARCH volatility volatilities may be simply mistaken for an integrated process[3].

3.2. The MFIAPARCH model

With reference to Conrad *et al.* (2010), Bauwens (2006) and Bollerslev (2009)[4], we expose the MFIAPARCH model with DCC and CCC specifications. To do so, we consider a N-dimensional column vector of emerging stock market returns $r_{i,t}$ for the country at the time t and for the country i,

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[1] The authors showed that "(i) even if all parameters are nonnegative, the conditional variance can become negative and (ii) even if all parameters are negative (apart from *d*), the conditional variance can be nonnegative almost surely. In particular, the conditions for the (1, *d*, 1) model substantially enlarge the sufficient parameter set provided by Bollerslev and Mikkelsen (1996, *Journal of Econometrics 73*, 151–184). The importance of the result is illustrated in an empirical application of the FIGARCH(1, *d*, 1) model to Japanese yen versus U.S. dollar exchange rate data" (Conrad and Haag, 2006, 413). For more details see Conrad and Haag (2006) cited within references.

[2] For further details, see Table 1 in Brooks, R.D. R.W. Faff, M. D. McKenzie and H. Mitchell (2000). A multi-country study of power ARCH models and national stock market returns. Journal of International Money and Finance, 19, 377-397.

[3] Regarding this point, see also Diebold and Rudebusch (1991).

[4] Bollerslev (2009) has presented a glossary for ARCH/GARCH models in Volatility and Time Series Econometrics: Essays in Honour of Robert F. Engle, Eds. T. Bollerslev, J. R. Russell and M. Watson.

$\boldsymbol{r_t} = [r_{it}]_{i=1,\ldots,N}$ and the $\varepsilon_{i,t}$ are the residual terms vector from an AR(1) process, $\boldsymbol{\varepsilon_t} = [\varepsilon_{it}]_{i=1,\ldots,N}$. The structure of the multivariate AR(1) mean equation of stock returns is as follows:

$$Z(L)r_t = c + \varepsilon_t \tag{4}$$

$c = [c_i]_{i=1,\ldots,N}$ denotes the constant vector with $|c_i| \in [0,\infty)$. $\boldsymbol{Z}(L) = diag\{\xi(L)\}$ is a $N \times N$ diagonal matrix with $\xi(L) = [1 - \xi_i L]_{i=1,\ldots,N}, |\xi_i| < 1$. As in Conrad *et al.* (2010), we suppose that the residual term vector $\boldsymbol{\varepsilon_t}$ is governed by the relation:

$$\boldsymbol{\varepsilon_t} = e_t \otimes h\wedge_t^{1/2} \tag{5}$$

$\otimes$ denotes the Hadamard product while $\wedge$ is the elementwise exponentiation. $\boldsymbol{h}_t = [h_{it}]_{i=1,\ldots,N}$ is $\sum_{t-1}$ measurable and the vector $\boldsymbol{e_t} = [e_{it}]_{i=1,\ldots,N}$ is governed by an (i.i.d.) with mean zero and positive definite covariance matrix $\boldsymbol{\rho} = [e_{it}]_{i=1,\ldots,N}$ with $\rho_{ij} = 1$ for $i = j$. The above equation implies that $\boldsymbol{E}(\boldsymbol{\varepsilon_t}|F_{t-1}) = 0$

and

$$\boldsymbol{H}_t = E(\boldsymbol{\varepsilon_t}\boldsymbol{\varepsilon_t}'|F_{t-1}) = diag\{\boldsymbol{h}\wedge_t^{1/2}\}\rho diag\{\boldsymbol{h}\wedge_t^{1/2}\}$$

Therefore, $\boldsymbol{h}_t$ denotes the vector of conditional variances and $\rho_{ij} = h_{ij,t} \big/ \sqrt{h_{i,t}h_{j,t}}, i,j = 1,\ldots,N$ are the constant conditional correlations.

Next, the MFIAPARCH (1,d,1) is written as follows:

$$B(L)\left(h\wedge_t^{\frac{\delta}{2}} - \omega\right) = [B(L) - \Delta(L)\Phi(L)][I_N + \Gamma_t]|\varepsilon_t|\wedge^{\delta} \tag{6}$$

Where $\boldsymbol{B}(L) = diag\{\beta(L)\}$ with $\beta(L) = [1 - \beta_i L]_{i=1,\ldots,N}, |\beta_i| < 1$. $\Phi(L) = diag\{\Phi(L)\}$ with $\boldsymbol{\Phi}(L) = [1 - \Phi_i L]_{i=1,\ldots,N}$, $|\Phi_i| < 1$. Moreover, $\omega = [\omega_i]_{i=1,\ldots,N}$ with $\omega_i \in (0,\infty)$ and $\Delta(L) = diag\{\boldsymbol{d}(L)\}$ with $\boldsymbol{d}(L) = [(1-L)^{d_i}]_{i=1,\ldots,N}$, $0 \le d_i \le 1$. Furthermore, $\Gamma_t = diag\{\gamma \otimes s_t\}$ with $\gamma = [\gamma_i]_{i=1,\ldots,N}$ and $s_t = [s_{it}]_{i=1,\ldots,N}$, where $s_{it=1}$ if $\varepsilon_{it} < 0$ and 0 otherwise.

In the present study, it will be appealing to research for a more appropriate distribution for the stock market innovation's process. In this perspective, Aggarwal *et al.* (1999) revealed that in contrast with developed stock markets, returns in emerging markets exhibit positive asymmetry and subsequently student-t distribution could be more suitable for emerging countries. Additionally, it is well documented that the Gaussian density provides an inconsistent estimator (see, Newey and Steiggerwald, 1997, Brooks *et al.* 2000) and it will be evident to relax the normality assumption. According to Harvey *et al.* (1992), Fiorentini *et al.* (2003) and Bauwens *et al.* (2006) the Student density can be considered as an accepted alternative to the normal distribution for the stock return innovations. With reference to these authors, the Student-t distribution has an extra scalar degrees of freedom parameter, denoted ν hereafter. It should be noted that when this parameter tends to infinity, the Student density tends to the normal density. When it tends to zero, the tails of the density become thicker and thicker and can consider for extreme values in the stock return volatility (Bauwens *et al.*, 2006, p. 97)[5]. Under this assumption, the Student density can be defined as[6]:

[5] According to Bauwens et al. (2006), the parameter value indicates the order of existence of the moments, e.g. if $\nu = 2$, the second-order moments do not exist, but the first-order moments exist. For this reason, it is convenient (although not necessary) to assume that $\nu > 2$, so that H_t is always interpretable as a conditional covariance matrix (Bauwens *et al*. 2006).

[6] For more details see Bauwens *et al.* (2006) cited within references.

$$g\left(z_t|\theta,\upsilon\right)=\frac{\Gamma\left(\frac{\upsilon+N}{2}\right)}{\Gamma\left(\frac{\upsilon}{2}\right)\left[\Pi\left(\upsilon-2\right)\right]^{\frac{N}{2}}\left[1+\frac{z_t^{'}z_t}{\upsilon-2}\right]^{-\frac{N+\upsilon}{2}}} \tag{7}$$

Where $\Gamma(.)$ is the Gamma function

4. Data source and preliminary analysis

4.1. Data

In this research, we employ daily closing stock indexes for four emerging countries from the LA region; namely Argentina (MERVAL), Brazil (BOVESPA), Chile (IGPA) and Mexico (IPC). Stock indexes are expressed in local currency. They cover the period from 2nd January 1995 to 15th September 2009, giving a total of 4,035 observations. It should be stressed that, in line with Edwards (2000) and Chen *et al.*'s (2002) studies, we have deliberately excluded the Mexican financial crisis known as the 'Tequila' of the 1994 from our sample period for at least two main reasons. First of all, the 'Tequila' turmoil volatility spillovers across LA stock markets were largely discussed in the literature. Secondly, the economic contagion and volatility spillovers may generate spurious dependencies across stock markets which could bias our findings related to dynamic inter-linkages across LA stock markets. The data set was extracted from the Datastream International (Thomson Financial). It is useful to note that in order to avoid any spurious correlation between stock market indexes, given that the holiday days are not common with the LA stock markets, we have removed all the common holidays, concomitantly, and we replaced by zero all the stock returns corresponding to the non-common holidays. In this way, we preserved all the available points in time.

In the reminder of this study, the continuously compounded returns (r_t) are computed as follows:

$$r_t=100\times\left[ln\,P_{i,t}-ln\,P_{i,t-1}\right] \tag{8}$$

Where $P_{i,t}$ is the price level of market *i* at time *t*, *ln* is the natural logarithm operator. Summary statistics for the selected emerging stock returns are displayed in Table 1. From this table, we can perceive that all the stock returns are skewed to the left. It is worth noticing that the LA stock market return exhibits high values of kurtosis. This implies that the selected stock market behavior presents some extreme values. The Jarque Bera (1980) test statistic indicates a significant departure from the normal distribution. Overall, LA stock returns are not governed by a normal distribution. The Ljung Box (1978) statistic on the first twenty lags $LB(20)$ of the sample autocorrelation function is significant for all the daily returns indicating the presence of serial correlation. Also, we have carried Engle's (1982) LM ARCH (values are not reported here) test for the squared residuals. This test reveals the existence of heteroscedasticity for all the LA stock market returns. Fig. 1 plots the stock return behavior for each market. With exception to Chile, the reported plots reveal a clustering of larger return volatility. In the financial time series modeling, it is well admitted that this phenomenon can be described by GARCH-class models.

Table 1. Descriptive statistics of the stock market returns

Stock index	Mean	Variance	Skewness	Excess Kurtosis	J-B	$LB(20)$
MARVEL	0.0119	2.2836	-1.0714 *** (27.112)	16.852*** (213.27)	46160.***	45.8307**
BOVESPA	0.0428	2.4652	-0.087768*** (2.2209)	8.2662*** (104.61)	10935.***	109.440**
IGPA	0.0218	1.2407	-0.21251***	11.947***	22859.***	238.601**

			(5.3776)	(151.20)		
IPC	0.0371	1.9698	-0.12758***	8.4258***	11366.***	69.9998**
			3.2283	(106.63)		

Notes: The sample period is totaling 3840 daily observations. (***), (**), and (*) denote statistical significance at 1%, 5% and 10% levels, respectively. All the stock returns are computed as the first differences of the natural log of stock indices times 100. J-B is the Jarque-Bera (1980) normality test statistic. $LB(20)$ is the Ljung-Box statistics with up to 20-day lags.

Not surprisingly, these preliminary results are typically consistent with previous investigations on the emerging stock markets's dynamics. Besides we implemented some conventional unit root and stationarity test results for all the selected stock market returns. With reference to the Augmented Dickey Fuller (1979) (ADF) and the Phillips-Perron (1988) (PP)[7] unit root tests, we can undoubtedly reject the hypothesis of unit root for the five time series returns at 1% significance level. It should be indicated that the bandwidths in the unit root test were allowed to vary across individual countries so as to mop up any residual serial correlation. The bandwidth was based on Newey–West using the Barlett Kernel spectral estimation method. Furthermore, whether or not a time trend is included in the unit root test estimation, the PP test shows that the first differences of all the time series are stationary. All the emerging stock market indexes time series turned out to be integrated in the same order. Also, the KPSS test results indicate that we cannot reject the null hypothesis of stationarity at 1% significance level for all the stock returns. Hence, all the return series are stationary, I(0) and suitable for long memory tests.

4.2. Testing long memory in stock market volatilities

As in major previous works, we consider two proxies of daily volatility squared returns and absolute returns. Various long-memory tests are implemented in order to detect an eventual long-memory; namely Lo's (1991) test, the rescaled variance (V/S) test of Giraitis *et al.* (2003) and two semiparametric estimators of long memory parameter, the log-periodogram regression (GPH) of Geweke and Porter-Hudak (1983) and the Gaussian semiparametric (GSP) of Robinson (1995)[8]. The test results are displayed in Table 3. Regarding these results, we can conclude that for all the selected emerging markets, there's no long-range memory in the mean return's equations. According to the V/S, we can not reject the null hypothesis of no long memory since the computed statistic is over the critical value[9]. Moreover, with reference to Robinson (1995) GSP and GPH test statistics, (Panels A and B), we reject the null hypothesis of long-memory for a significance level of 1% for absolute and squared returns. Subsequently, all the selected emerging market volatilities seem to be governed by a fractionally integrated process. Overall, we conjecture that clustering volatility, fat tails, asymmetry and long-range memory characteristics should be considered in econometric modeling of emerging stock market volatilities.

Table 2. Long memory test results

m	Argentina	Brazil	Chile	Mexico
Panel A: GPH (1983) test				
Absolute return $\lvert r_t \rvert$				
m=$T^{0.5}$	0.563	0.523	0.518	0.527

[7] To reserve space, the unit-root and stationarity test results are not presented here, but are available upon request.

[8] The choice of these alternative tests is justified by the fact that several authors cautioned about using Lo's (1991) modified R/S in isolation. More precisely, several Monte Carlo experiments conducted by Teverovsky, Taqqu and Willinger (1999) and Willinger, Taqqu and Teverovsky (1999) on Lo's (1991) statistic found that the modified R/S statistic is based in favor of accepting the null of no long range dependence as the bandwidth increases.

[9] For the Geweke and Porter-Hudak's (1983) test it has been implemented with different bandwidths $m = T^{0.5}, T^{0.6}, T^{0.8}$. Likewise, the Gaussian semiparametric (GSP) test of Robinson (1995) was estimated for diverse bandwidths $m = \frac{T}{4}, \frac{T}{16}, \frac{T}{64}$.

m=$T^{0.6}$	0.598	0.548	0.516	0.501
Squared return r_t^2				
m=$T^{0.5}$	0.501	0.459	0.457	0.5612
m=$T^{0.6}$	0.532	0.514	0.468	0.418
Panel B: GSP Robinson (1998) test				
Absolute return $\lvert r_t \rvert$				
m=T/4	0.392	0.377	0.411	0.315
m=T/16	0.611	0.575	0.543	0.535
Squared return r_t^2				
m=T/4	0.354	0.321	0.412	0.215
m=T/16	0.532	0.481	0.472	0.436
Panel C: Rescaled variance test				
Absolute return $\lvert r_t \rvert$				
m=5	2.001	1.988	2.315	1.247
m=10	3.318	3.217	3.747	1.832
Squared return r_t^2				
m=5	1.899	1.785	2.143	1.324
m=10	3.012	2.546	3.457	1.878

Notes: (r_t), (r_t^2), and $|r_t|$ are respectively log return, squared log return and absolute log return. (m) denotes the bandwidth for the Geweke and Porter-Hudak's (1983) and the GSP Robinson (1998) tests.

4.3. Unconditional correlation analysis

It is reasonable to start our investigation by analyzing the simple pair-wise unconditional correlation between the selected emerging stock market returns. The unconditional correlation matrix is given in Table 3.

Table 3. The unconditional correlation matrix for the stock returns

	MARVEL (Argentina)	BOVESPA (Brazil)	IGPA (Chile)	IPC (Mexico)
MARVEL-Argentina	1.000	0.87***	0.88***	0.89***
BOVESPA - Brazil	0.87***	1.000***	0.97***	0.97***
IGPA – Chile	0.88***	0.97***	1.000	0.97***
IPC – Mexico	0.89***	0.97***	0.97***	1.000***

Notes: MARVEL, BOVESPA, IGPA and IPC are the national stock indexes for respectively Argentina, Brazil, Chile and Mexico. Stock returns are daily frequency and cover the period January, 1995-September 2009. (***) denotes the significance at 1% level.

From the significance probabilities, we perceive high unconditional correlations within the LA stock markets. It is worthily emphasized that Chile, Brazil and Mexico exhibit the highest unconditional correlations. For example, the correlation between Brazil and Chile is equal to 0.97. A similar correlation is observed between Mexico and Brazil. For Argentina, the computed unconditional correlations are relatively lower than the other countries. The correlations for the pairwises (Argentina- Brazil); (Argentina-Chile) and (Argentina-Mexico) are respectively equal to 0.87, 0.88, and 0.89.

To provide more insights into LA stock market interactive linkages during the period under study, we have graphed (Fig. 1) their stock price indexes over time. As prescribed in Fig.1, the selected LA stock markets were trembled by some major financial crisis during the sample period. Indeed, sudden collapse of some foreign exchange rate values (Russian's Rouble devaluation, October 1998) (Ø), the Brazilian real devaluation, January 1999) and the recent US subprime crisis (October 2008) have occurred. For the Asian financial crisis, it has emerged on July 1997 and it was considered as the most severe financial crisis not seen since the 1987 crash. According to Bownan and Comer

(2000), the Asian turmoil has most important consequences in terms of volatility and contagion effects. Chen *et al.* (2002) revealed that it has the major effects on global security markets (Chen *et al.*, 2002, p. 1120). For example, late in October 1997, the substantial turn down in Asian stock markets, particularly in the Hong Kong stock market, has triggered high negative stock returns especially in Argentina, Brazil and Mexico. On 30th October, 1997, the latter markets recorded -9.38%, -7.25% and -6.47% respectively. Lower negative return was perceived in Chile (-1.07%). In October 1998, the Russian financial crises occurred and created dramatic volatility spillovers on all the LA stock markets. In fact, in Argentina, Brazil, Chile and Mexico, the stock markets have rapidly responded to bad news relative to the devaluation of the rouble (Russian local currency) and the capital outflows from Russia. More precisely, on 10th September 1998, high negative daily returns of -11.19%, -14.69%, 5.56%, -3.65% were observed for respectively the MARVEL, BOVESPA, IGPA and IPC LA stock indexes. Three months ago (January, 1999), Brazil facing its own financial crisis, devalues its currency, hurting Argentine exports, 30% of which were traded with Brazil. According to Chen *et al.* (2002), the Brazilian real devaluation has brought turmoil to the LA stock markets (Chen *et al.*, 2002, p. 1121). For example, on 13th January 1999, the BOVESPA stock index went from 48.64 to 38.95 points leading the other stock market returns to a dramatic drop of -9.79% for the MARVEL index, -4.70% for the IGPA index and -7.03% for the IPC stock index. It seems that the Brazilian financial crisis has the major effects on the other LA major stock markets. The Brazilian real devaluation was negatively perceived by stock market traders and portfolio managers. In addition, the Argentinean Financial crisis also occurred in our sample period. More specifically, late in December 2001, Argentina announced that it can no longer guarantee payment on foreign debt. Our sample period includes the 11/9 terrorist attack as an international extreme event which has a major effect on global equity markets. LA stock markets were negatively affected by this event. Our stock return time series show a substantial decline for all the selected markets. For example, the Brazilian stock market dropped down with -7.41% on 12th September 2001. In January, 6th 2002, the Argentinean monetary authorities announced the end of the currency board and a plan to devalue the local currency (peso) by 29% (to 1.4 to the US dollar) for major foreign commercial transactions, with a floating rate for all other transactions. Few days ago, the peso fell as low as 2.05 to the dollar in the foreign exchange market. On the stock market, the MARVEL stock index return jumped down to -27.48%. It is worthily mentioned that the Argentinean financial crisis had spillover effects on the other major LA stock markets. Lower negative daily stock returns were perceived in Brazil, Chile and Mexico. It should be stressed that the time frame of our study includes the largest movements which is US subprime (October, 2008) and subsequent global financial crisis. It should be noted that sharp negative returns were perceived during the first signs of subprime worries in October 2007. Later on this month, stock market returns have shown a decline of -3.33%, -2.10%, -2.96% and -1.88% in Argentina, Brazil, Chile and Mexico respectively.

Figure 1.
Latin America stock markets behavior over time

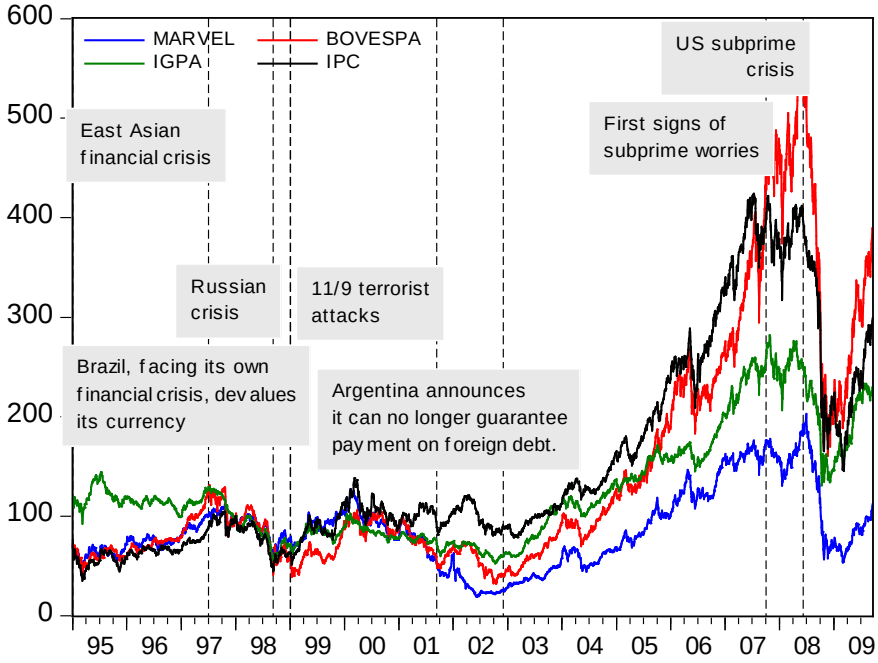
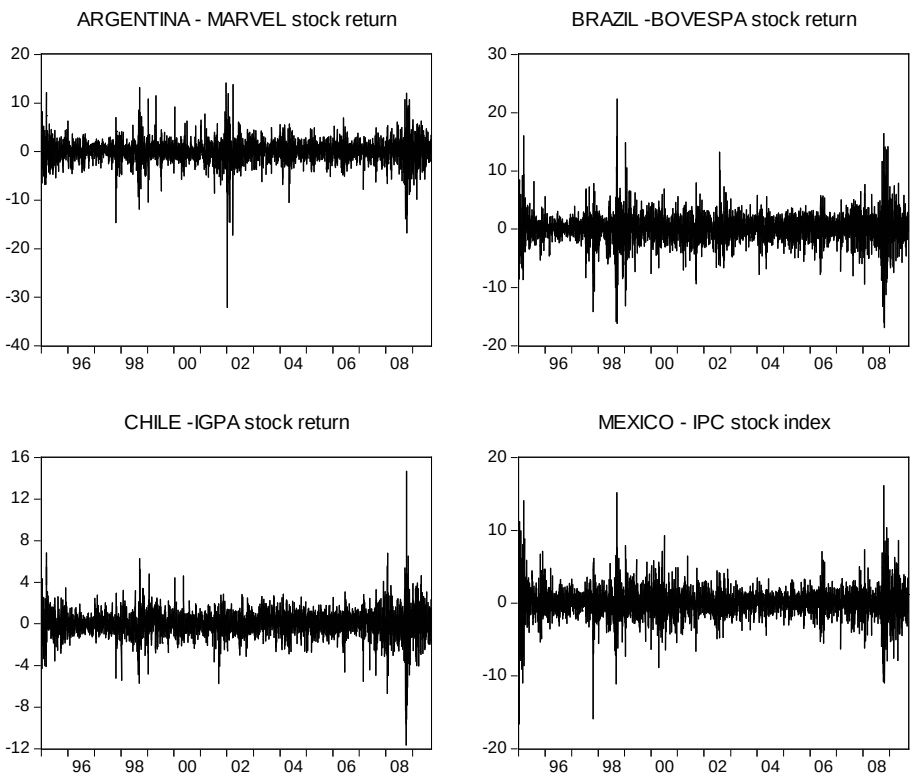


Fig. 2 plots daily stock returns. From this figure, volatility clustering is noticeably apparent for all the time series: large (small) changes tend to be followed by large (small) changes over consecutive day, revealing the presence of heteroscedasticity. All these characteristics are a common motivation for the employ of ARCH/GARCH models to adequately describe emerging stock market returns volatility dynamics.

Figure 2 – LA daily stock returns (daily frequency, January 1995-September 2009)



5. Estimation results

5.1. The univariate AR-FIAPARCH specification

In Table 4, we report the estimation results of the AR-FIAPARCH model of BBM (1996) with Student-t errors. This model is estimated by Approximate (Quasi-) Maximum Likelihood (for more details see Laurent and Peters, 2002), since it allows for asymptotically valid inference when the standardized innovations are not normally distributed (Tansuchat *et al.*, 2009, p. 14). It should be noted that the estimating results are obtained using the BFGS algorithm. We employed the Ox/G@RCH 6.01 econometrics software package of Laurent and Peters (2007). As mentioned above, we employed a Student–t distribution for the stock return innovations. In line with prior works including Aloui and Mabrouk (2010), Beine (2002), Niguez (2007) and Conrad (2010), we consider that the Student-t distribution constitutes an appropriate alternative for the Gaussian distribution[10]. Therefore, for the univariate models, the log-likelihood to be maximized is given by (Davidson, 2008):

$$log\ I = T\left[log\ \Gamma\left(\frac{\upsilon+1}{2}\right) - log\ \Gamma\left(\frac{\upsilon}{2}\right) - \frac{1}{2} log\ \pi(\upsilon-2)\right] - \frac{1}{2}\sum_{t=1}^{T}\left\{ log\ h_t^2 + (\upsilon+1)\left[log\left(1+\frac{\varepsilon_t^2}{h_t^2(\upsilon-2)}\right)\right]\right\} \quad (8)$$

Surprisingly, using Akaike (AIC), Hannan-Quinn (HQIC) information criteria and log-likelihood LR test we found that the AR(1)-ARFIMA(1,d,1) is appropriate for all the selected stock market indexes. For this specification, all the selected countries, the AR coefficients are highly significant. In addition, for four stock markets, the coefficients γ measuring the leverage effect are highly significant. This result indicates the presence of a negative correlation between stock returns and volatility. Also, for all the selected markets, the estimation results reveal statistically significant power terms. Brazil and Mexico exhibit the highest power terms with respectively 0.6374 and 0.7231. For the other emerging countries, the power term parameter ranges from 0.1886 to 0.2804. Interestingly, all the emerging stock markets display highly significant differencing fractional parameters indicating a high degree of persistence behavior. This implies that the impact of shocks on the conditional volatility of stock market returns consistently exhibits a hyperbolic rate of decay. Additionally, Mexico, Chile and Brazil exhibit quite similar fractional parameter. For these countries, the fractional parameter is equal to 0.347617, 0.347290 and 0.309858 respectively. These countries seem to share a common degree of fractional integration while for Argentina; the fractional parameter is moderately higher (0.450942). In this country, this finding corroborates Safadi and Pereira (2010) and Costa *et al.*'s (2010) results. They found that the FIAPARCH specification provides a good fit for the Argentine stock market daily volatility.

Further, the Student-df parameter is highly significant for all the stock markets. This result confirms our preliminary analysis and subsequently the choice of the Student-t distribution as an appropriate alternative to the Gaussian counterparts. Concerning the goodness-of-fit tests (see Panel B), our results relate that we do not reject the null hypothesis of a correct model specification since the Ljung-Box and the RBD test statistics computed, with 10 lags, show no serial correlation and no remaining ARCH effect. Thus, there's no evidence of statistical misspecification. Further, all the ARCH parameters satisfy the non negativity condition set for the conditional variance (see Conrad, 2010). In summary, the AR(1)-FIAPARCH(1,d,1) estimation results indicate that it is well appropriate to describe emerging stock market dynamics. Indeed, the FIAPARCH model seems to be able to consider for three major stylized facts in stock market behaviour (1) volatility is highly persistent, (2) volatility responds to price movements asymmetrically, and (3) the power of returns for which the predictable structure in the volatility pattern is the strongest should be determined by the data (Kim *et al.* ; 2005).

5.2. Fractional integration or asymmetric power arch effects

Hitherto, it's commonly admitted in the literature that emerging stock market returns exhibit long memory in their conditional variance behavior. Some empirical works including Barkoulas *et al.* (2000), Wright (2001), Kilic (2004), Vougas (2004), Floros (2007) Floros *et al.* 2008), Kang and Yoon (2007), Kasman *et al.* (2009) have shown the applicability of FIGARCH and FIAPARCH models to describe emerging markets volatility. However, as mentioned above, there's no consensus for the truly integrated dynamics for the conditional variance (Baillie *et al.*, 1986). On the other hand, the univariate FIAPARCH models estimating results indicate that the selected LA markets' volatilities

[10] It should be mentioned that the selected models are estimated under the normal innovation's distribution. Our main objective is to check the robustness of our estimation to the choice of the density functions.

are governed by fractional integration processes. Specifically, the fractional integration parameter is highly significant for all the cases. In order to check whether stock market volatilities are truly modeled by the fractional differencing parameter, we employed the Wald test. The main idea is to check whether we are in presence of stable APARCH model $(d=0)$ or IAPARCH model $(d=1)$. The Wald test results are displayed in Table 5.

Table 5. Wald test results for the fractional integration power term parameter's linear restrictions

Null hypothesis	d	Wald test		γ	Wald test	
		$d=0$	$d=1$		$\gamma=0$	$\gamma=1$
Argentina	0.4509	23 [0.000]	121 [0.000]	0.2077	14 [0.000]	111 [0.000]
Brazil	0.3098	31 [0.000]	76 [0.000]	0.6374	22 [0.000]	102 [0.000]
Chile	0.3472	51 [0.000]	37 [0.000]	0.2804	31 [0.000]	47 [0.000]
Mexico	0.3476	46 [0.000]	41 [0.000]	0.7231	43 [0.000]	87 [0.000]

Notes: For each LA stock market index, we report the value of the Wald statistic (Wald test) for the linear restrictions on $d=0,1$ and $\gamma=1,2$ in the FIAPARCH model. The numbers between brackets are the p-values.

As shown in Table 5, the Wald statistics are highly significant and reject both the stable APARCH and IAPARCH specifications for all the cases. Indeed, the Wald statistics show that the asymmetric power parameters are significantly superior to one. Also, the fractional integration coefficients are significantly different from 0 and 1. In the light of these results, the FIAPARCH model seems to be appropriate to describe conditional variance behavior of the LA stock markets. However, it is worth noticing that this result should be confirmed by an out of sample forecasting performance. This main question passed over intentionally in this study and may be apprehended in a future research.

From an economic view, our findings will bring further implications especially for portfolio management, stock market efficiency and asset pricing. For portfolio management, Cheung and Lai (1995) and Wilson and Okunev (1999), among others, proved that portfolio allocation decisions may become particularly sensitive to the investment horizon. There may be diversification benefits in the short and medium terms, but not if the assets are correlated over the long term if long memory is present. In this case, stock prices tend to reverse their trends in the short term creating thus short-term trading opportunities. On the other hand, it is well known that if the stock price volatility is governed by a long memory process, the arrival of new information cannot be fully arbitraged away. Additionally, in the context of stock market efficiency, it is also known that the possibility of speculative profits as a result of superior long range dependence model forecast would cast doubt on the basic tenets of market efficiency (Härdle and Mungo, 2008, 214).

5.3. The bi and quadrivariate FIAPARCH model results

5.3.1. The bivariate specifications

In this sub-section, we estimate a MFIAPARCH-DCCE specification in order to analyze the volatility spillovers between the selected LA emerging stock markets. To do so, we estimate the FIAPARCH specification for all the pair-wise stock markets: (Argentina, Brazil), (Argentina, Chile), (Argentina, Chile), (Brazil, Chile), (Brazil, Mexico) and (Chile, Mexico). We have to mention that we have estimated several specifications using the Maximum Likelihood Estimation (MLE) as suggested by Davidson (2008). Moreover, all the models are estimated using a Student–t distribution for the stock market return innovations. The estimation results are displayed in Tables 4.A and 4.B. We employed jointly the SIC, AIC, HQIC information criteria, and likelihood ratio test to select the best fitting bivariate specifications. Accordingly, the FIAPARCH(1,d,1) is selected for all the stock markets except for Brazil. For this country, the information criteria and the likelihood tests came out with a (0,d,1) for the FIAPARCH specification. Further, in all the cases, the AR(1) coefficients are highly significant. As in the univariate models, the β parameter is statistically significant. In all the cases, the fractional differencing parameter is highly significant. Surprisingly, all the pair-wise stock markets exhibit very similar fractional differencing parameters. For example, (0.3178; 0.3122) and (0.2889; 0.3166) are the fractional parameters for (Argentina, Mexico) and (Brazil, Chile) respectively.

Moreover, the leverage term γ is highly significant for all the stock markets. The estimated values range from 0.22 to 0.58. In all cases, the power terms δ are highly significant. The FIAPARCH specification generates quite similar power terms for (Argentina, Brazil) (2.06; 2.02) and for (Argentina, Mexico) (1.59, 1.57). Furthermore, the DCC COR_{ij} is highly significant for all the stock market pair-wises. The highest correlations are perceived between Argentina and Brazil and between Argentina and Mexico. Concerning the degree of freedom parameters, our results reveal that they are statistically significant at 1% level in all cases. Also, the ARCH parameters satisfy Conard's conditions. Finally, it is indispensable to check whether the selected index time series exhibit evidence of multivariate ARCH effects and to test ability of the MFIAPARCH specification to capture the volatility spillovers between emerging markets. Compared to the various diagnostic tests devoted to univariate GARCH-class models, only few tests are reserved to the multivariate counterparts. This point of view is confirmed by Kroner and Ng (1998). The authors noted that "the existing literature on multivariate diagnostics is sparse compared to the univariate case" (Bauwens *et al.*, 2006, p.100). In their paper, Bauwens *et al.* (2006) have surveyed the diagnostic tests specific to the MGARCH-class models. In the present study, we referred to the most widely employed diagnostic tests, namely (a) the Ljung-Box statistics for standardized and squared univariate model residuals, (b) the multivariate Ljung-Box test statistic suggested by Hoskin (1980) and (c) the Li and McLeod's multivariate Portmanteau statistics on squared standardized residuals (see panel C).

Table 5.A - Estimation results for the univariate AR-FIAPARCH specification under student-t innovation's distribution (QMLE)

	Argentina	Brazil	Chile	Mexico
Panel A: Estimation results				
$Const.(M)$	0.038960 **	0.096705***	0.018105	0.070911***
	(2.098)	(3.137)	(0.9614)	(2.805)
$AR(1)$	0.080480***	0.131300***	0.216220***	0.117527***
	(4.199)	(8.627)	(13.25)	(7.389)
$Cst.(\upsilon)$	0.215625***	0.288229***	0.074451***	0.149959***
	(2.277)	(3.901)	(2.701)	(3.690)
$d-figarch$	0.450942***	0.309858***	0.347290***	0.347617***
	(3.014)	(6.353)	(4.659)	(6.464)
$Arch$	0.200283 ***	0.039412*	0.249705***	0.209592***
	(2.429)	(0.4537)	(2.988)	(3.801)
$Garch$	0.513626***	0.254713***	0.455954***	0.482070***
	(3.410)	(2.351)	(3.626)	(6.125)
$Aparch(\gamma)$	0.207768***	0.637474***	0.280424***	0.723183***
	(2.330)	(5.654)	(5.278)	(5.609)
$Aparch(\delta)$	1.870320***	1.498471***	1.812368***	1.405326***
	(10.44)	(14.74)	(18.03)	(12.68)
$Student-df$	6.645432***	7.270414***	9.165147***	7.120888***
	(7.22)	(8.963)	(6.761)	(8.744)
$Log.lik.$	-7962.015	-8431.580	-5797.492	-7546.686
Panel B: Diagnostic tests				
AIC	3.321455	3.432261	3.765546	3.412233
HQIC	3.657734	3.478991	3.770045	3.754707
$Q(20)$	27.3472	19.4450	42.2735	20.7472
	[0.0968]	[0.4286]	[0.0016277]**	[0.3509342]
$Q^2(20)$	33.0757	20.4732	11.3035	8.79327
	[0.0163]*	[0.3068]	[0.8810356]	[0.9643409]
$Arch(5)$	F(10,3816)=	F(5,4017) =	F(5,4017) =	F(5,4017) =
	1.2299	1.2862	0.45311	0.37045
	[0.2660]	[0.2668]	[0.8113]	[0.8692]
$RBD(10)$	11.9064	8.07959	2.21848	4.53102
	[0.2913]	[0.6210]	[0.9943748]	[0.9202297]

Notes: For each of the emerging stock index, we report the estimation results of the AR(1)-FIAPARCH model with QMLE estimations. (***), (**) denote the significance level at 1% and 5% respectively. Q(.) is the Ljung-Box statistics for squared standardized residuals. AIC is the Akaike (1974) information criterion. HQIC is the Hannan-Quinn information criteria. RBD(10) is the residual based diagnostic for conditional heteroscedasticity at 10 lags. P-values are in brackets. Student-t-values are reported in parentheses. Df is student-df.

Table 5 B. The bivariate AR-FIAPARCH (DCC-Engle) model estimation results under Student-t innovation's distribution

	Argentina-Brazil		Argentina-Chile		Argentina-Mexico	
	Argentina	Brazil	Argentina	Chile	Argentina	Mexico
Panel A: Estimation results						
$AR(1)$	0.0596	0.0596***	0.0475***	0.2034***	0.0405***	0.0786***
	(4.097)	(8.182)	(3.093)	(12.89)	(2.703)	(5.334)
$d-figarch$	0.2057*	0.0769***	0.3495***	0.3203***	0.3178***	0.3122***
	(6.437)	(5.776)	(5.167)	(4.263)	(5.472)	(6.749)
$Arch$	0.3632***	-	0.2142***	0.2780***	0.2023***	0.2118***
	(2.663)		(2.964)	(3.321)	(2.788)	(3.930)
$Garch$	0.2493***	0.2293***	0.4666***	0.4620***	0.4313***	0.4633***
	(2.605)	(2.324)	(4.483)	(3.687)	(4.356)	(6.562)
$Aparch(\gamma)$	0.3107***	0.4796***	0.3298***	0.2212***	0.3686***	0.5697***
	(4.163)	(4.870)	(4.167)	(4.162)	(4.190)	(5.096)
$Aparch(\delta)$	2.0612***	2.0266***	1.5882***	1.8406***	1.5980***	1.5764***
	(30.92)	(31.81)	(11.05)	(15.19)	(11.35)	(13.20)
Panel B. Conditional correlation						
$COR.ij$	0.568*** (7.19)		0.367*** (9.91)		0.433*** (6.750)	
df	0.483***	(13.50)	6.645*** (12.29)		6.236*** (13.54)	
Panel C. Diagnostic tests						
$Q(20)$			30.6245	37.1624	23.3749	17.3892
			[0.060]	[0.0111]	[0.2707]	[0.627]
$Q^2(20)$			68.4223	8.00887	77.1237	10.5588
			[0.0000003]	[0.9918]	[0.0000]	[0.9568]
Hoskin (20)	120.346	[0.0018]	149.243	[0.0001]	136.607	[0.0000]
Hoskin(20)	145.310	[0.0000]	134.826	[0.0000]	122.020	[0.0017]
Li-McLeod(20)	120.296	[0.0019]	149.157	[0.0000]	136.586	[0.0000]
Li-McLeod(20)	145.172	[0.0000]	134.681	[0.0000]	121.915	[0.0010]

Notes: $COR.ij$ is the conditional correlation between stock market (i) and (j). The numbers in parentheses are t-statistics. $Q(20)$ $Q^2(20)$ denote the 20th order Ljung-Box tests for serial correlation of standardized and squared standardized residuals respectively. The numbers in brackets are p-values.

Table 5.B. The bivariate AR-FIAPARCH (DCC-Engle) model estimation results under Student-t innovation's distribution

	Brazil -Chile		Brazil-Mexico		Chile-Mexico	
	Brazil	Chile	Brazil	Mexico	Chile	Mexico
Panel A: Estimation results						
$AR(1)$	0.0952*** (6.913)	0.1942*** (13.14)	0.0907*** (6.80)	0.0770*** (5.59)	0.1976*** (13.35)	0.0850*** (5.87)
$d-figarch$	0.2889*** (6.215)	0.3166*** (4.629)	0.2950*** (6.50)	0.3134*** (7.14)	0.3188*** (5.02)	0.3348*** (7.07)
$Arch$	-	0.2710*** (3.403)	-	0.2720*** (5.40)	0.2831*** (3.655)	0.2934*** (6.91)
$Garch$	0.3031*** (3.115)	0.4560*** (3.801)	0.3230*** (3.04)	0.5115*** (7.64)	0.4771*** (4.29)	0.5556*** (9.66)
$Aparch(\gamma)$	0.5218*** (5.542)	0.2337*** (4.575)	0.5245*** (5.50)	0.5587*** (5.09)	0.2397*** (4.60)	0.5844*** (5.28)
$Aparch(\delta)$	1.5399*** (15.86)	1.7774*** (16.81)	1.5018*** (15.82)	1.5607*** (14.06)	1.7419*** (16.19)	1.5085*** (13.37)
Panel B. Conditional correlation						
$COR.ij$	0.4904*** (19.31)		0.315738*** (3.514)		0.431675*** (12.47)	
df	8.2507*** (11.42)		7.3737*** (12.42)		8.496617*** (10.94)	
Panel C. Diagnostic tests						
$Q(20)$	21.76 [0.3534]	34.11 [0.0253]	14.59 [0.7984]	20.56 [0.4231]	38.56 [0.0075]	24.93 [0.203]
$Q^2(20)$	19.79 [0.4709]	9.45 [0.97701]	32.73 [0.0360]	10.76 [0.9520]	12.82 [0.8841]	14.33 [0.8135]
Hoskin (20)	135.87 [0.0000]		126.223 [0.0005]		142.386 [0.0000]	
Hoskin(20)	109.86 [0.0101]		158.160 [0.0000]		74.1071 [0.6038]	
Li-McLeod(20)	135.82 [0.0000]		126.200 [0.0005]		142.298 [0.0000]	
Li-McLeod(20)	109.86 [0.0101]		158.185 [0.0000]		74.1734 [0.6017]	

Notes: $COR.ij$ is the conditional correlation between stock market (i) and (j). The numbers in parentheses are t-statistics. $Q(20)$ $Q^2(20)$ denote the 20th order Ljung-Box tests for serial correlation of standardized and squared standardized residuals respectively. The numbers in brackets are p-values.

5.3.2. Quadrivariate specifications

Table 6 displays the estimation results of a quadrivariate DCC-FIAPARCH models. The parameters of interest are displayed in Panel A; while the diagnostic tests are given in Panel B. As mentioned above, the use of M-FIAPARCH-DCC specification allows to analyze the dynamic adjustment over time for three LA emerging markets. Moreover, the DCC specification takes into account the eventual shifts in the conditional correlation over time. Using the likelihood ratio test and the minimum value of the various information criteria, we have selected a FIAPARCH(1,d,1) specification for all the stock markets. From these estimations, some interesting comments can be made. From Panel A., the autoregressive parameter is statistically significant at 1% for all the stock markets. Also, the power parameter APARCH δ is highly significant. It ranges from 1.5428 (Brazil) to 1.7780 (Chile). Similarly, the fractional integration parameter is highly significant for the stock markets. The estimated values range from 0.275223 (Brazil) to 0.3009 (Chile). This result is consistent with the univariate and the bivariate specifications (see, Table 2). However, it is worthily to note that the estimated values fractional integration parameters are lower than their counterparts in the univariate and the bivariate models. More importantly, the coefficient APARCH γ assessing the leverage effect is highly significant. In all cases, the DCC and the degrees of freedom (□) are statistically significant at 1% level. Table 1 provides some stochastic properties of the computed DCC's. It may provide more insights into the degree of volatility spillovers for pairwise stock market. It is worthily to note that the conditional correlations between Latin stock markets are highly significant indicating strong volatility spillovers between them. With reference to Conrad and Haag (2006), our results indicate that the

ARCH parameters are statistically significant and ensure the necessary conditions to ensure the non-negativity of the conditional variances. Overall the trivariate FIAPARCH-DCC estimation results are quite similar to their bivariate counterparts. These results could be compared to Conrad *et al.*'s findings (2010)[11]. The authors concluded that the trivariate FIAPARCH-CCC results are typically similar to those issued from the bivariate specification.

Table 6. The quadrivariate DCC- FIAPARCH (BBH) model estimation results (under Student-t innovation's distribution)

	ARG	BRZ	CHL	MEX
Panel a. Estimation results				
AR(1)	0.024017*	0.072623*	0.184260*	0.055706*
	(1.751)	(5.905)	(12.62)	(4.264)
Cst(v)	0.245824*	0.365567*	0.104162*	0.148610*
	(3.865)	(4.668)	(3.475)	(4.400)
d-figarch	0.306823*	0.275223*	0.300945*	0.281891*
	(5.542)	(6.587)	(4.683)	(6.988)
ARCH	0.256987*	0.184859*	0.311278*	0.303389*
	(3.644)	(2.680)	(4.558)	(6.599)
GARCH	0.482356*	0.394509*	0.495752*	0.526842*
	(5.058)	(4.472)	(4.878)	(9.349)
APARCH(□)	0.295652*	0.467897*	0.202155*	0.512026*
	(3.864)	(5.452)	(3.934)	(4.306)
APARCH(□)	1.657027*	1.542835*	1.778043*	1.671042*
	(11.94)	(15.70)	(13.53)	(13.37)
Df		8.292817		
		(15.26)		
Panel C: Diagnostic tests				
Hoskin (20)		462.407	[0.0000003]	
Hoskin(20)		442.802	[0.0000044]	
Li-McLeod(20)		462.241	[0.0000003]	
Li-McLeod(20)		442.758	[0.0000044]	

5.4. Are the selected models robust to the stock return innovation's distributions?

In this sub-section, we check the robustness of MFIAPARCH estimating results to the choice of the stock return innovation's distribution. As in Conrad *et al.* (2010), the selected models are estimated under the Gaussian density and QMLE. For space scarcity, these results are not reported here, but they are available upon request. Broadly speaking, we perceive that the estimating results are typically similar to their counterparts under student-t innovation's distribution. More interestingly, the fractional differencing and the power ARCH parameters are similar to those obtained with Student-t error distribution and MLE. Moreover, it should be noted that, as in estimations under Student-t distribution, the hypotheses of $d = 0$ and $d = 1$ as well as $\delta = 1$ are strongly rejected. With reference to the information criteria, our results confirm the choice of the FIAPARCH model to capture long memory and asymmetries in the stock market volatilities. From a comparative view, our results are ambiguous. In fact, according to the SIC, AIC, HQIC and SHIC test statistics, the selected models estimated under the Student-t distribution and MLE outperform their counterparts with Gaussian error's distribution and QMLE. However, the likelihood ratio tests display the same values for the two error's distributions. This result is confirmed for both the univariate, bivariate and quadrivariate specifications. Also it reinforces our choice for the Student-t innovation's distribution as an appropriate alternative to the normal distribution. Our outcomes are analogous to Conrad *et al.* (2010) findings. In fact, the authors attested that their selected FIAPARCH models are robust to the choice of

[11] As we noted above, it is the only published research employing the MFIAPARCH-CCC in order to assess volatility spillovers between stock markets.

the stock return innovation's distribution but they do not deliver definitive conclusions supporting the Student-t distribution.

5.4.1. The DCC behavior around financial crisis

In the present study, we employed the conditional correlations generated by the quadrivariate FIAPARCH specification in order to provide more accurate details in relation to stock market volatility spillover. Our choice is motivated by at least two points. Firstly, with reference to Conrad *et al.* (2010), the MFIAPARCH specification exhibits better predictive performance than the univariate and bivariate specifications (for more details see Conrad *et al.*, 2010, p. 9). More precisely, using some forecast evaluation criteria including mean square error (MSE), adjusted mean absolute percentage error (AMAPE), the authors showed that the MFIAPARCH specification has the best statistics. Accordingly, the M-FIAPARCH model has sufficient empirical validity across different stock emerging and developed stock markets. Secondly, we employed the Akaike (AIC), Shwartz (SIC), and Hannan-Quinn (HQIC) or Shibata (SHIC) (values are reported in the univariate, bivariate and quadrivariate estimation results) in order to rank[12] the various specifications. According to these criteria, the quadrivariate seems to be the optimal specification for all the LA stock markets.
In Table 7 we report some descriptive statistics of the conditional correlations of the six pair-wise stock markets under research. All the pair-wise stock markets exhibit positive conditional correlation. The higher means of conditional correlations correspond to Argentina and Brazil and between Brazil and Mexico. Argentina and Chile exhibit the lowest conditional correlation mean value (0.3675). It should be noted that higher conditional correlations are associated to extreme movements. The skewness, kurtosis and the Jarque-Béra test statistics indicate that all the pair-wise DCCs exhibit significant departure from the normal distribution. The kurtosis statistic reveals that the DCCs time series are highly leptokurtic; this can be attributed to the presence of some extreme events in the DCCs behavior over the sample period. This observation is approved by Fig. 3 prescribing the pair-wise conditional correlations dynamics.

Table 7. Statistic properties of the MFIAPARCH- DCC's

Pair-wise countries	Min.	Mean	Max.	Std. Dev.	Skewness	Excess Kurtosis
ARG-BRZ (COR.12)	0.12393	0.53842	0.76755	0.14245	-0.82988 (21.000)	0.11190 (1.4161)
ARG-CHL (COR.13)	0.1057	0.3675	0.6297	0.12199	0.13767 (3.4837)	-0.72680 (9.1981)
ARG-MEX (COR.14)	0.13421	0.45244	0.7312	0.14228	-0.29341 (7.4246)	-0.66182 (8.3758)
BRZ-CHL (COR.23)	0.17477	0.47141	0.68151	0.09926	-0.37108 (9.3901)	0.012357 (0.15639)
BRZ-MEX (COR.24)	0.29208	0.55713	0.77773	0.11904	0.13436 3.3999	-0.95049 12.029
CHL-MEX (COR.34)	0.15231	0.41863	0.6868	0.11312	0.18728 (4.7392)	-0.64380 (8.1478)

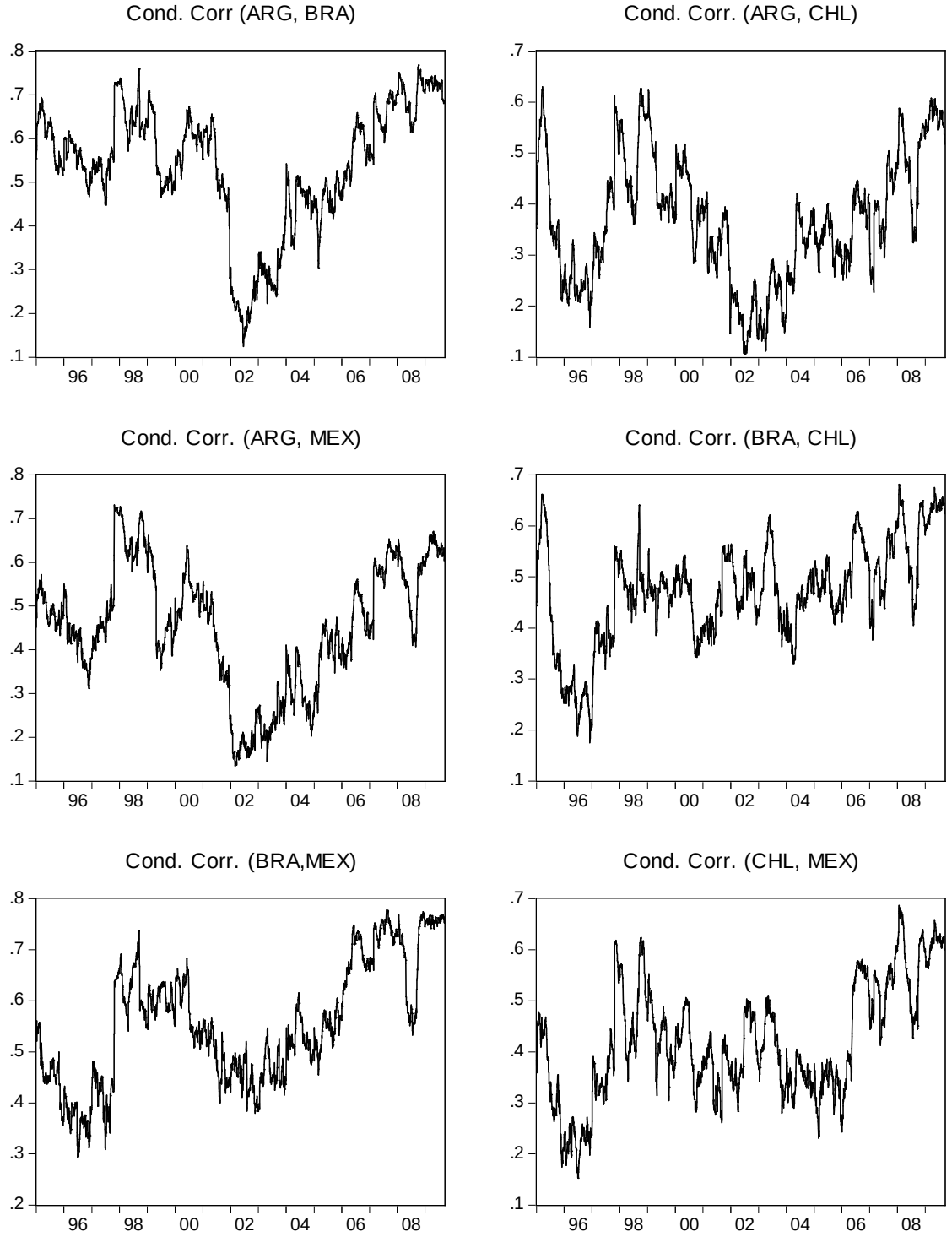
Notes: S.D. is the standard deviation. Figures in parentheses are the Student-t statistics.

Some clear patterns seem to merge from this figure. First of all, for the period under research, the conditional correlations are extremely volatile with some jumps over time. This observation is in line with the stochastic properties of the M-FIAPARCH-DCC's reported in Table 7. For all the markets, the conditional correlations exhibit high standard deviations. Moreover, the excess kurtosis and the asymmetry in the DCC's distributions may be explained by the presence of extreme values. Secondly, we should note that the conditional correlations between the four stock markets display a quite similar tendency over the sample period. For these pair-wise stock markets, the conditional correlations share the same long-run tendency. Starting from January 1995 up to the end of 1996 these conditional correlations were going down varying within limits from 0.62 to 0.46 for the pair-wise (Argentina, Brazil) and from 0.52 to 0.20 for (Argentina, Chile). Similar pattern is observed for the other stock

[12] In this study, the relative ability of the various univariate and MFIAPARCH models to predict LA emerging stock market daily volatility is deliberately passed over.

market pair-wises. During the period 1997-2002, the conditional correlations exhibit a significant increase with an extremely high volatility. It is worthily to stress that the conditional correlations display a high volatility jump during the regional stock financial crisis.

Figure 3. The conditional correlation behavior over time



5.5. *The DCCs shifts behavior around financial crisis*

In light of previous descriptive analysis, we perceive that the conditional correlations between LA emerging stock markets have shown to be persistently higher and exhibit significant increases around regional and international financial crisis. The outcome of this research will bring further practical

side, this result may have potential implications for portfolio managers and hedge funds active in LA stock markets. More precisely, it is well known that a higher level of correlations may reduce diversification's benefits. Further, since conditional correlations exhibit higher volatility level, portfolio mangers will be reserved to employ the estimated correlations for portfolio asset's allocations[13]. For this, it is essential to provide more accurate details on the conditional correlation shifts behavior around financial crisis periods. A detailed statistical analysis of the conditional correlations time series is necessary in order to detect eventual shifts behavior associated to various LA financial crises during the sample period. To do so, we employed the GARCH model to describe the DCC's volatility and we included dummy variables in both DCC mean and conditional variance equations. Using dummy variables corresponding to major LA financial crises allows us to capture volatility shifts during financial crisis periods. In concordance with some prior studies including among other Chiang *et al.* (2007), we estimated the following mean equation to describe DCC behavior.

$$\rho_{ij,t} = \sum_{p=1}^{P} \psi_p \rho_{ij,t-p} + \sum_{k=1}^{5} \beta_k dum_{k,t} + \eta_{ij,t} \tag{9}$$

Where $\rho_{ij,t}$ is the pair-wise conditional correlation between the stock returns of Argentina, Brazil, Chile and Mexico, such that (i) corresponds to Argentina while (j) corresponds to Brazil, Chile and Mexico. Overall we total six pair-wise countries. We employed the AIC and SIC information criteria to specify the optimal lag length in the conditional correlation mean equation. For the dummy variables, we have subdivided the whole sample period (January 1995- September 2009) into five sub-periods based on the dates of major financial crises. It should be stressed that our sample period is large and included various financial crisis such in Asia, Russia, Argentina, Brazil, United States as well as some geopolitics events such as September 11, 2001 terrorist attacks, 2003 Iraqi invasion. In the present study, the focus is on some major domestic financial crisis as well as the recent US subprime crisis.

Table 8. The whole sample subdivision

Selected subsamples	Pre and post LA and international financial crisis
1/1/1995-11/17/1997	Pre Asian financial crisis
11/18/1997- 13/1/1999	Post Asian financial crisis and prior to Brazilian financial crises
1/14/1999- 01/06/2002	Post Brazilian financial crisis and prior to Argentinean financial crisis
01/07/2002 -10/13/2008	Post Argentinean crisis and prior to US subprime crisis
10/13/2008-09/15/2009	Post subprime crisis

The estimating results of the conditional correlation mean equation are related in Table 9. With reference to the LM-ARCH tests, all the conditional correlations time series exhibit strong evidence of heteroscedasticity. For this reason, we estimated, as in Chiang *et al.* (2007), a GARCH(1,1) model to describe the conditional variance dynamics. Further, we included the dummy variables in order to test for volatility shifts behavior. Formally, the conditional variance equation is written as follows:

$$h_{ij,t} = \alpha_0 + \alpha_1 h_{ij,t-1} + v_1 \eta^2_{ij,t-1} + \sum_{k=1}^{5} d_k dum_{k,t} \tag{10}$$

According to this model, the significance of the dummy variables' coefficients in the mean or/and the conditional variance implies the presence of shifts in the conditional correlation dynamics around the international or/and domestic financial crises. The GARCH(1,1) estimates within the maximum-likelihood method are displayed in Table 9. Panels A and B report the mean and the variance equations estimation respectively while diagnostic tests are shown in Panel C.

[13] Similar arguments were also given by Chiang et al. (2007).

Table 9. GARCH(1,1) model of the conditional correlation dynamics during financial crisis

	(ARG-BRA) COR.12	(ARG. CHL) COR.13	(ARG.MEX) (COR.14	(BRA-CHL) COR.23	(BRA-MEX) COR.24	(CHL-MEX) COR.34
Panel A. the mean equation						
Constant	0.0013***	0.0011***	0.0012***	0.0013***	0.0011***	-0.016***
	(3.456)	(4.655)	(3.243)	(4.032)	(6.768)	(-6.999)
ρ_{t-1}	0.998***	0.9980***	0.9981***	0.9945***	0.9968***	0.993***
	(158.647)	(104.1)	(62.6)	(42.9)	(67.08)	(87.31)
$dum_{1,t}$	-0.0001	0.0011	0.0012	0.0018	0.0011	0.0180
	(-0.246)	(1.576)	(1.589)	(0.970)	(1.501)	(1.098)
$dum_{2,t}$	-0.0004	0.0004	0.0012	0.0025*	0.0020*	0.0189
	(0.941)	(0.875)	(1.122)	(0.966)	(2.105)	(1.154)
$dum_{3,t}$	0.0001	0.0008**	0.0002	0.0024*	0.0017*	0.0194
	(0.434)	(2.343)	(0.260)	(2.060)	(2.004)	(1.186)
$dum_{4,t}$	-0.0002	0.0011*	0.0008	0.0028	0.0020**	0.01925
	(-0.501)	(1.692)	(1.287)	(1.478)	(2.508)	(1.174)
$dum_{5,t}$	0.0024	0.0005*	0.0015	0.0034*	0.0026*	0.0200
	(0.243)	(1.687)	(1.468)	(1.248)	(2.304)	(1.223)
Panel B. the variance equation						
Constant	-4.55E-05***	-2.69E-05	-5.21E-06	-3.78E-05***	-1.67E-05	4.50E-05***
	(-4.947)	(-0.313)	(-1.036)	(-36.833)	(-0.136)	(77.363)
h_{t-1}	0.049***	0.064***	0.244***	0.088***	0.190***	0.136074***
	(27.142)	(9.403)	(30.534)	(13.936)	(24.142)	(22.220)
η^2_{t-1}	0.681***	0.529***	0.103***	0.600***	0.345***	0.572376***
	(10.661)	(9.391)	(11.865)	(19.605)	(20.686)	(28.187)
$dum_{1,t}$	6.63E-05***	6.70E-05	7.06E-05***	6.65E-05***	6.87E-05	-1.60E-05***
	(7.343)	(0.781)	(14.252)	(39.342)	(0.563)	(-10.643)
$dum_{2,t}$	6.62E-05***	6.18E-05	4.56E-05***	6.69E-05***	5.01E-05	-1.43E-05***
	(7.406)	(0.720)	(8.656)	(29.529)	(0.411)	(-6.974)
$dum_{3,t}$	7.09E-05***	8.71E-05	9.85E-05***	7.94E-05***	5.60E-05	1.85E-05***
	(7.961)	(1.014)	(17.949)	(32.204)	(0.459)	(6.577)
$dum_{4,t}$	6.73E-05***	7.14E-05	7.14E-05***	6.51E-05***	4.86E-05	-1.24E-05***
	(7.534)	(0.832)	(14.371)	(39.347)	(0.399)	(-8.648)
$dum_{5,t}$	5.23E-05***	4.67E-05	3.19E-05***	4.81E-05***	2.56E-05	-3.80E-05***
	(5.761)	(0.544)	(5.989)	(65.405)	(0.210)	(-112.721)
Panel C. Diagnostic tests						
Q(5)	2.113	1.543	3.554	2.766	3.877	1.987
ARCH(5)	0.7888	0.5198	1.311	0.665	0.435	1.0322

Notes: The lag length is determined by the AIC criterion. Q(10) is the Ljung-Box Q-statistics up to five days, testing the serial correlation of the residuals. ARCH(5) is the ARCH LM test up to five days, testing the heteroscedasticity of the residuals. (***), (**), and (*) denote the statistical significance at 1%, 5%, and 10% levels, respectively. Numbers in parentheses are Z-statistics.

From the variance equation estimates (Panel B), it can be seen that for all the pair-wise countries, the dummy variables are positive and highly significant for all the selected financial crises dates. This indicates more volatile fluctuations in the conditional correlations around the financial crisis. However, the dummies 3, 4 and 5 seem to have positive and significant impact on the conditional correlation mean equation for the conditional correlations between Argentina and Chile, between Brazil and Chile and between Brazil and Mexico (see Panel A). Put it another way, financial crisis in Argentina and Brazil as well as the recent US subprime crisis have significantly increased correlations between these countries. These results suggest that when the crisis occurred in one market, the correlation could vary intensely and this variability seems to be persistent over time. According to the arguments of Chiang *et al.* (2007), "when any public news about one country is interpreted as information for the entire region, the correlation becomes more significant" (Chiang *et al.*, 2007, p. 1220). Further, our results are consistent with our preliminary analysis of the DCC behavior over time (see Fig. 3). On the practical side, it would be crucial to consider for the conditional correlation behavior shifts in any model devoted to equity risk management. Our results are in line with prior studies including among others Forbes and Rigobon (2002), Chiang *et al.* (2007).

5.6. *Are the conditional correlations cointegrated over time*?

In this sub-section the attention is focused on the behavior over time of the conditional correlations. More specifically, we examine whether the pair-wise stock market DCCs have the tendency to move towards a long run equilibrium (i.e. cointegrated). In terms of time series modeling, any eventual long-run equilibrium relationship between stock market pair-wise DCC allows to provide more insights into the short-run adjustment mechanism and its short-run responses to volatility shocks over time via an error correction model (VECM). The main important feature of the VECM model is the impulse response functions and the variance decomposition. The impulse response function constitutes a pertinent approach to analyze the behavior of impulse response function induced by variables in the VECM model. More interestingly, our analysis could be completed by a forecast error variance analysis. The variance decomposition may provide more expedient details about the proportion of the DCC fluctuation explained by its own shocks opposed to shocks from other variables. The variance decomposition technique will be a precise approach since our main objective is to examine the volatility spillovers behavior across LA stock markets evolved by financial events occurring during from mid-1990s onwards.

5.6.1. Unit root and cointegration tests

For unit-root tests, we implemented the Augmented Dickey Fuller (ADF) (1979) and the Phillips and Perron (PP) (1988) tests. The use of the latter test is justified since we have detected autocorrelation and ARCH effects in the DCC's behavior over time (see, descriptive statistic in Table 4). It is well known that the PP unit root test is robust to strong autocorrelation and heteroscedasticity in the time series. We should mention that the bandwidths in the unit root tests are allowed to vary across pair-wise stock LA markets and they are based on the Newey-west using Bartlett Kernel spectral estimation method. The unit-root test results are displayed in Table 5. From these results, we record that whether or not a time trend or constant is injected in the unit root test regression, the ADF and the PP tests reveal that the first difference of the MFIAPARCH-DCC's are stationary. Thus, all the DCCs turned out to be integrated in the same order (I(1)). Since unit roots are prescribed for all the conditional correlations, it will be possible to perform the Johansen's multivariate cointegration tests. The underlying idea is to check whether any DCC's combinations are cointegrated over time. The multivariate coinegration test results are shown in Table 11.

Table 10. ADF and PP unit root tests for the conditional correlations

Country's pair-wise	ADF		PP	
	levels	first difference	levels	first difference
(ARG, BRA)	-2.005	-25.82***	-2.000	-60.94***
(ARG, CHL)	-2.74	-26.20***	-2.921	-60.43***
(ARG,- MEX)	-2.08	-26.50***	-2.069	-61.35***
(BRA, CHL)	-3.97	-40.14***	-2.941	-59.94***
(BRA, MEX)	-2.96	-41.09***	-3.142	-60.84***
(CHL, MEX)	-3.51	-40.74***	-2.58	-60.72***

Notes: The ADF (Augmented Dickey–Fuller), the first differencing ADF, PP (Phillip-Perron), and the first differencing PP tests should be compared. The critical values for the rejection of the null hypothesis of a unit-root are -3.451, and -2.870 for 1% and 5%, respectively. (***) denotes the rejection of the null hypothesis at 5% and 1% significance levels.

5.6.2. The multivariate cointegration test results

For our comments we refer to the Trace statistic test and the max-Eigen test statistics. According to these tests, we can identify six cointagration's(Ø) vectors at 5% significance level. This result is consistent with our preliminary analysis relative to the pair-wise conditional correlations behavior over time. Using these outcomes, it is possible to estimate a VECM in order to analyze the DCC's short-run adjustments between the LA stock markets.

Table 11. Tests of unrestricted cointegration rank

Hypothesized no. of CE(s)	Trace statistic	5% critical value	Max-Eigen Statistic	5% critical value

None	123.9285*	95.7536	38.5164	40.07757
At most 1	85.4121*	69.8188	29.4801	33.8768
At most 2	55.9319*	47.8561	23.0390	27.5843
At most 3	32.8929*	29.7970	22.5318*	21.1316
At most 4	16.3610*	15.4947	6.4122	14.2646
At most 5	3.9288*	3.8414	3.9228*	3.8414

Notes: (*) denotes rejection of the null hypothesis at the 5% significance level.

5.6.3. The DCC's interactive relation over time

Six DCCs are included in the VECM. It should be noted that the lag selection is decisive for the VECM specification. It is well known that if the lag length (p) is too small, the VECM will be unable to describe the data generating process. On the contrary, if the lag length is too large, the VECM may suffer from over parameterization. For our study, we employ the AIC and the SBC information criteria in order to determine the VECM optimal lag length. According to these criteria, 1 and 6 lag lengths are selected. The estimation of the VECM(1) and VECM(6) delivered typically similar results. For space scarcity only the VECM(1) is considered[14].

[14] The VECM(6) results are available upon request.

Fig. A - Response of COR.12 to Cholesky One S.D. Innovations

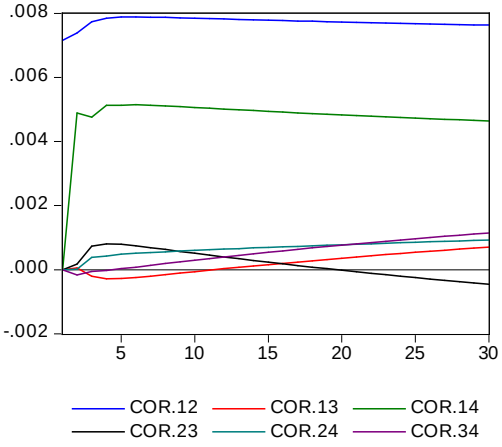


Fig. B- Response of COR.13 to Cholesky One S.D. Innovations

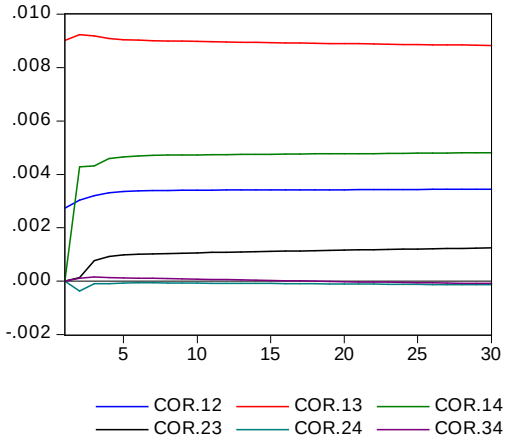


Fig. C- Response of COR.14 to Cholesky One S.D. Innovations

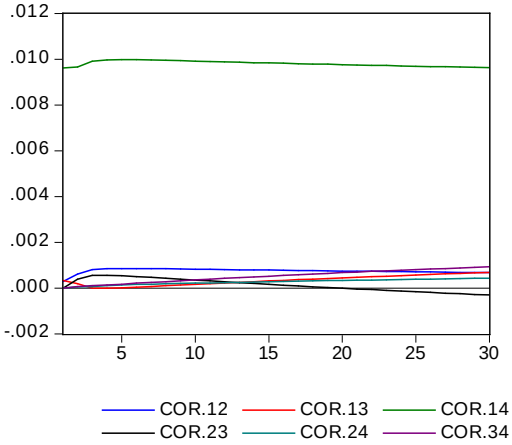


Fig. D - Response of COR.23 to Cholesky One S.D. Innovations

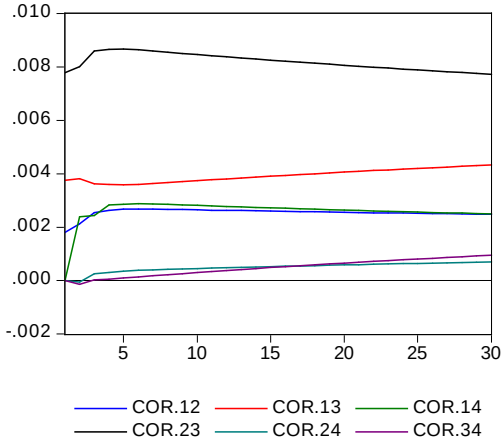


Fig.E - Response of COR.24 to Cholesky One S.D. Innovations

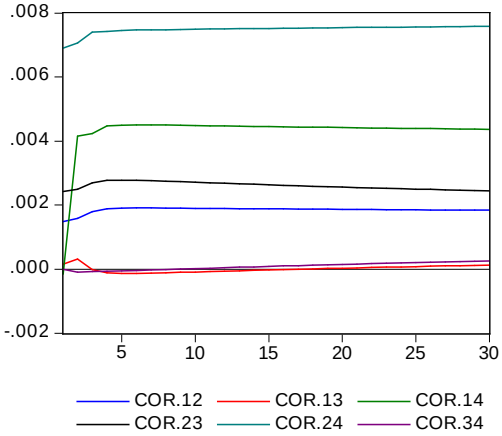


Fig. F - Response of COR.34 to Cholesky One S.D. Innovations

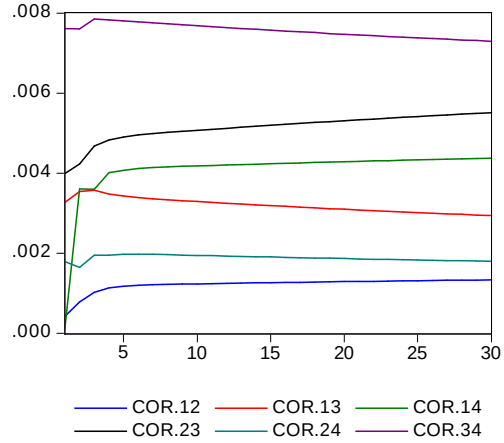


Fig. A illustrates the responses of COR.12 (Argentina, Brazil) to shocks from the other variables. As it can be discerned from this figure, the COR.12 responses to itself have increased during the first five days and then turn to be constant with a value of 0.0078. This result is quite similar to previous studies including Erbaykal and Okuyan (2008). Using a Choleski variance decomposition, the authors found that a shock on MERVAL affects positively BOVESPA. The response of the shock to the conditional

correlation between Argentina and Mexico (i.e. COR.14) reached 0.004 during the first day and then turned to be constant for a 30-day-time horizon. Put it another way, the conditional correlation between Argentina and Brazil seems to be affected by its counterparts between Argentina and Mexico. This can be regarded as an interactive linkage between these stock markets.

Fig. B shows the COR.13 responses to shocks. Broadly speaking, the COR.13 is sensitive to itself. Up to 2 days, the response of COR.13 is positive and constant with 0.009. The conditional correlation between Argentina and Mexico (COR.14) impinged positively during the first two days from 0.001 to 0.0041 and was 0.0043 for the rest of the time-horizon. The response of the COR.13 to the conditional correlation between Argentina and Brazil (i.e. COR.12) was constant over time with 0.0031 up to two days. From Fig. C describing the COR.14 (Argentina, Mexico) responses to shocks, we see that a COR.12 response to itself is constant time with positive value: 0.10. For the other DCCs shocks, the COR.12 responses are positive but slightly weak. In other words, the conditional correlation between Argentina and Mexico is *a priori* not weakly affected by the other DCCs shocks. The response of COR.23 (Brazil, Chile) to itself is positive and remained in the same level for all the selected day-ahead's (see Fig. D). More interestingly, we note that for a positive shock to COR.14 (Argentina, Mexico), the response of COR.23 increased from zero to 0.0028 in the first five days and was 0.0025 for the rest of the time-horizons. Hence, the dynamic linkage between Brazil and Chile stock markets is affected by shocks in the dynamic correlation between Argentina and Mexico. This result clearly shows that the four stock markets are implicated in the contagion phenomenon in the LA region. Similar to other correlation responses, the COR.24 (see Fig. E) shows positive and constant responses to itself: 0.007 to 0.0075 and remains constant up to three days. Furthermore, the COR.24 responses to COR.14 (Argentina, Mexico) shocks impinged positively: 0.0001 to 0.004 in the first two days and remained constant. A quite similar tendency is observed for COR.12 and COR.23. They remained constant with respectively 0.0018 and 0.0022. The conditional correlation between Chile and Mexico (COR.34) is positively influenced by chocks occurring on conditional correlation between all the selected stock markets. COR.12 and COR.14 have positive effect on COR.34 (see, Fig. F). More importantly, COR.34 responds positively to COR.14 shocks; it goes from 0.0001 to 0.004 during the first five days. Furthermore, COR.34 responses positively to its own shocks with.

In summary, the pair-wise DCCs response impulse functions clearly indicate that the LA emerging stock markets are closely linked in terms of volatility. From a financial view, the information about risk in the neighboring emerging markets is transmitted across LA region. The variance decomposition analysis may provide greater details about the dynamic volatility spillovers among these stock markets. In the empirical literature several techniques have been employed to provide further details to the MGARCH-DCC's behavior over time. Broadly speaking, these empirical studies involved diverse methodologies including: state Markov switching regime models, GJR-GARCH modeling, DCC's break point tests, traditional Choleski variance decomposition, the generalized decomposition method suggested by Pesaran and Shin (1998). In the present study, we adopt the orthogonalized method in order to provide more insights into the interactive relationships between the four emerging stock markets. It is well known that the variance decomposition is appropriate for our research question in the sense that it breaks down the variation in each pair-wise stock market DCCs into its components. It provides the proportion of stock market DCC's movements that are due to their own shocks versus shocks transmitted from other markets. It is generally anticipated that a variable can explain almost all its forecast error variances during short periods and smaller proportions in the long-run. We ordered the six DCCs time series in the VECM as follows: COR12, COR.13, COR.14[15], COR23, COR.24[16] and COR.34[17]. The variance decomposition results correspond to 1-day, 2-day, 5-day, 10-day, 15-day, 20-day, 25-day and 30-day ahead forecast error variance for each stock market pair-wise DCC. The VD results are displayed in Table 12. COR.12 seems to be largely autonomous in VD. COR.14 has an impact of 18.42% on output in the COR.12 after only two days and reached 27.53% after one month. The other conditional correlations have slightly weak impact on the dynamic correlation between Argentina and Brazil. As in COR.12, COR.13 was shown to be mostly autonomous in variance decomposition. More importantly, some other conditional correlations such as COR.12, COR.14 and COR.23 have an impact on COR.13. Particularly, COR.12 explained more than 8% variance after five

[15] COR.12, COR13 and COR.14 denote the dynamic correlations between Argentina and Brazil, between Argentina and Chile and between Argentina and Mexico.

[16] COR.23 and COR.24 denote the dynamic correlation between Brazil and Chile and between Brazil and Mexico.

[17] COR.34 denotes the dynamic correlation between Chile and Mexico.

days. Explicitly, the conditional correlation between Argentina and Brazil had an impact on its counterpart between Argentina and Chile. Financial risk is jointly transmitted from Argentina to Brazil and Chile. This result is consistent with the profile of the impulse response functions. COR.14 has an impact of about 17% for the first ten days; while COR.23 affected slightly, about 1%, of COR.13. The reported results show that COR.14 was shown to be largely autonomous in variance decomposition. In fact, for a 2-day ahead, more than 99% of COR.14 variance is explained by its own variance. However, the contribution of the other conditional correlations in explaining COR.14 is 1%. Concerning COR.23 variance decomposition, we perceive that it is moderately autonomous. In fact, COR.23 is affected by its own shocks, with an average of 72% variance. Compared to the previous conditional correlations, COR.23 is strongly affected by COR.12, COR.13 and COR.14 with respectively 5.96%, 14.28% and 5.87% for 5-day ahead forecasting. Additionally, COR.24 is sensibly affected by its own volatility shocks with an average of 68%. Also, COR.14 variance is explained by 13.14% after 2 days and by 22.2% after one month. Quite similar findings are obtained for the COR.34 variance decomposition. Although it is moderately autonomous in variance decomposition, COR.34 is simultaneously affected by all the other pair-wise countries correlations. The contribution of each conditional correlation in explaining COR.34 variance ranges from 1% (COR.12) to 22% (COR.24).

Table 12. Comparison of the forecasting models

Variance decomposition	Horizon (days)	COR.12	COR.13	COR.14	COR.23	COR.24	COR.34
Argentina - Brazil (COR.12)	1	100.0000	0.000000	0.000000	0.000000	0.000000	0.000000
	2	81.52421	0.002470	18.42676	0.024790	0.000177	0.021594
	5	73.99503	0.050498	25.33151	0.471516	0.142933	0.008516
	10	71.74132	0.040355	27.47356	0.461012	0.254711	0.029047
	15	71.28526	0.030157	27.89496	0.352273	0.338454	0.098898
	20	71.14689	0.046830	27.91137	0.267330	0.417597	0.209981
	25	71.07259	0.090446	27.76571	0.221049	0.495718	0.354483
	30	70.99245	0.157422	27.53876	0.212653	0.573305	0.525409
Argentina-Chile (COR.13)	1	8.385367	91.61463	0.000000	0.000000	0.000000	0.000000
	2	8.242704	82.56719	9.106320	0.008023	0.070189	0.005577
	5	8.983967	75.96532	14.57232	0.436320	0.030395	0.011681
	10	9.477911	72.86705	16.94422	0.684632	0.016930	0.009258
	15	9.676736	71.69751	17.80459	0.801158	0.013379	0.006636
	20	9.798483	71.01312	18.28738	0.883699	0.012323	0.004995
	25	9.888055	70.52619	18.61730	0.951823	0.012282	0.004353
	30	9.960301	70.14230	18.86816	1.011892	0.012758	0.004583
Argentina-Mexico (COR.14)	1	0.093941	0.123448	99.78261	0.000000	0.000000	0.000000
	2	0.245784	0.082022	99.58864	0.079159	0.001895	0.002495
	5	0.526835	0.031417	99.19967	0.220388	0.008263	0.013424
	10	0.618700	0.021572	99.08470	0.203797	0.022071	0.049162
	15	0.628922	0.036718	99.03793	0.155836	0.036500	0.104096
	20	0.620490	0.067539	98.96649	0.118829	0.052329	0.174326
	25	0.605844	0.110144	98.86013	0.097903	0.069408	0.256575
	30	0.588979	0.161840	98.72123	0.092450	0.087446	0.348054
Brazil-Chile (COR.23)	1	4.191973	18.09655	0.000936	77.71054	0.000000	0.000000
	2	4.640039	17.16670	3.420599	74.75865	0.002515	0.011502
	5	5.965060	14.28183	5.872161	73.81486	0.059671	0.006424
	10	6.473359	13.71706	6.946134	72.71849	0.116599	0.028355
	15	6.617995	14.10886	7.187781	71.84982	0.159069	0.076468
	20	6.673457	14.71286	7.234719	71.03418	0.199152	0.145635
	25	6.693054	15.38365	7.209079	70.24343	0.238918	0.231866
	30	6.694334	16.07332	7.150305	69.47158	0.278729	0.331736
Brazil-Mexico (COR.24)	1	3.968642	0.046661	0.040390	10.55235	85.39195	0.000000
	2	3.579744	0.097240	13.14286	9.167066	74.00629	0.006795
	5	3.883347	0.041206	19.41147	8.968751	67.68978	0.005451
	10	4.034250	0.027149	21.39353	8.787588	65.75459	0.002899
	15	4.061834	0.018857	21.92175	8.573691	65.42036	0.003518
	20	4.061179	0.014134	22.11814	8.364218	65.43494	0.007386
	25	4.050462	0.012235	22.18970	8.165499	65.56813	0.013975

	30	4.035475	0.012611	22.20267	7.978716	65.74777	0.022757
Chile-Mexico (COR.34)	1	0.201120	12.15494	0.014457	18.12901	3.652025	65.84844
	2	0.405659	12.07585	6.757771	17.57730	3.077106	60.10631
	5	0.828286	11.02290	10.78413	18.97685	3.215964	55.17187
	10	1.052624	10.16944	12.74240	20.12985	3.233405	52.67227
	15	1.148547	9.716290	13.53511	20.92748	3.198165	51.47441
	20	1.211791	9.375710	14.03691	21.61422	3.152334	50.60903
	25	1.261258	9.088733	14.41678	22.23911	3.104444	49.88968
	30	1.303112	8.835460	14.72997	22.81881	3.057117	49.25553

5. Discussions and major implications

In this study, we have examined the dynamic conditional relationships between four major LA stock markets using a MFIAPARCH model under the Student-t error distribution and vector error model (VECM). Our main research question is to test out the applicability of long-memory multivariate models to capture volatility spillovers among LA stock markets. In other words, we examined whether considering for some volatility stylized facts such as long memory and asymmetry would provide more insights into the contagion phenomenon in LA region. Some important implications of LA stock markets' volatility spillovers are identified in this study. First of all, our results reveal that pair-wise conditional correlations are not constant but time-varying are consistent with previous studies including Diamandis (2008), Arouri *et al.* (2008). The analysis of the DCC behavior over time has shown increasing trends during the LA financial crises. This result is expected in the sense that we anticipate greater volatility spillovers and subsequently financial risk transmission during crisis periods. Some explanations are provided by Chiang *et al.* (2007). Indeed, when financial crisis occurred, portfolio managers panicked and rebalanced their portfolio from risky assets to free-risk assets. This behavior may be considered as the main source of impulsive increases in correlations between stock markets. Secondly, our multivariate cointegration tests showed that the DCCs share common trends over time and thus limiting room for long-run gains for diversification in the LA stock markets. Specifically, time-varying DCC's implies that international investors should monitor carefully the risk associated with the time varying benefits of portfolio diversification. In terms of economics, it is worthily to remind that structural changes in local or international economy potential affect the interactive linkage between stock markets. Shamsuddin and Kim (2003), Fujji (2005), Cheung and Westermann (2001), Billio and Pelizzon (2003), Westermann (2004) and Kim *et al.* (2005) have empirically showed that emerging stock markets' linkages are considerably altered by several structural changes in local economies. Our results supporting DCC's time varying may reinforce this main conclusion. Finally, all the impulse response functions and the variance decomposition analysis clearly show that all the conditional correlations are largely affected by their own volatility shocks.

6. Summary and some concluding remarks

The main purpose of this paper is to provide more insights into the volatility spillovers between four LA emerging stock markets; namely Argentina, Brazil, Chile and Mexico for the period January, 1995 – September 2009. Furthermore, since the four LA countries implemented a financial liberalization process in the late 1980s and early 1990s and have been largely affected by some regional and international financial crisis we were interested in studying whether considering for some stylized facts such as long memory and asymmetry in stock market volatility may provide more accurate details related to the dynamics interactive linkages among LA stock markets. Our investigation was conducted within multivariate long memory ARCH models and multivariate cointegration.

Specifically, we have extended as in Conrad *et al.* (2010) the standard univariate FIAPARCH model to multivariate counterparts and we examined the applicability of the MFIAPARCH model with dynamic conditional correlation (DCC) of Engle (1982) and Student-t distribution for the stock return's innovations in describing volatility spillovers among LA stock markets. Univariate, bivariate and quatrivariate FI(A)PARCH models are estimated under both Gaussian and Student-t error's distributions. Also, we have analyzed the computed condition correlations behavior over time in a multivariate cointegration framework. We employed the VECM, impulse response functions and the Choleski variance decomposition to offer more comprehensive analysis of the short-term interactive volatility linkages between LA equity markets.

There are some results that stem from our research. First of all, asymmetry, fat-tails and long-range memory are common facts on LA stock markets' volatility. Secondly, LA markets' volatility exhibit strong evidence of long-memory which can be captured by a FIAPARCH model.

Thirdly, our empirical investigation pointed out that all the selected markets exhibit jointly strong evidence of power effects and long-memory in the conditional variance. More interestingly, the Bolleslev/Schwert specifications are rejected in favour of the power formulation. According to our results, for LA equity markets' volatility dynamics, the FIAPARCH model is preferred to stable and integrated specifications. It is worthily to emphasize that the univariate FIAPARCH estimating results are supported by their counterparts in a multivariate context. Further, the similarity of the obtained results insinuates that the M-FIAPARCH seems to have a quite general validity across LA stock markets. We considered that M-FIAPARCH with DCC specification is appropriate to capture volatility spillovers and shifts in the conditional correlation behavior. For comparative purposes, our results corroborate Conrad *et al.*'s (2010) findings.

Finally, the conditional correlations are not constant but time varying and have shown increasing trends during the LA domestic financial crises and the recent global turmoil period. Moreover, the multivariate cointegration tests showed that the DCCs share common trends over time. More importantly, the pair-wise DCCs response impulse functions revealed that the LA emerging stock markets are closely linked in terms of volatility. This indicated that the information about risk in the neighboring emerging markets is transmitted across LA region. Furthermore, the variance decomposition analysis and the impulse response functions jointly showed that all the conditional correlations are largely affected by their own volatility shocks. A priori, structural changes in local or international economy potentially affect the interactive linkage between stock markets.

Overall, we believe that our findings provide a first stab to a comprehensive analysis of the volatility spillovers between LA emerging stock markets within a multivariate long-memory ARCH framework. Our results may have some major practical implications for portfolio managers, private and institutional investors as well as hedge funds operating in LA capital markets.

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