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U.S. and Latin American Stock Market Linkages

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Abstract: This paper examines whether the Latin American equity markets of Argentina, Brazil, Chile and Mexico have become more integrated with the US equity market. We empirically measure integration by finding the dynamic conditional correlation (DCC) between each market and that in the U.S. using a DCC multivariate GARCH model. We then track how these correlations evolve over time using a smooth transition model which can not only show when greater integration first occurs but also how long it takes these correlations to transition to their new levels. Our sample period stretches from December 30th, 1988 to March 26th, 2004. Results show an increase in the degree of market integration between these countries and the U.S. Moreover, we find that the beginning of rapid integration coincides with the beginning of economic liberalization for Argentina and Brazil. For Mexico and Chile we find that the period of rapid integration is within the period of increasing bilateral trade.

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1. Introduction:

Has any structural change happened to the degree of comovement among North and Latin American equity markets? If so, when did the change occur and how long was the transition period? Answers to these questions are of a great importance for investors and policy makers. For investors the design of a well-diversified portfolio requires a clear understanding of how international stock returns are correlated and how these correlations change over time. Policy makers are concerned about correlations among equity returns and how these correlations evolve over time because of their role in the stability of the financial system in the region. It is now well documented that the potential gain from international diversification has been reduced due to the increase in the degree of comovement among equity markets (see for example Taylor and Tonks (1989), Eun and Shim (1989) and Campbell and Hamao (1992)). However, many studies have shown that emerging equity markets appear to provide better diversification opportunities due to their low correlations with developed equity markets (see for example Bekaert and Harvey (1995), Harvey (1995) and Korajczyk (1996)).

Emerging Latin American equity markets have became of great importance to international investors, especially to US investors, since the late 1980s and during the 1990s as these countries started to liberalize their equity markets during these periods. Moreover, the substantial increase in bilateral trade[†] between these countries and the US during the period from 1992 to 2003 have attracted attention of not only investors and policy makers but also of academic researchers due to the impact of international trade on equity market correlations. For example, Johnson and Soenen (2003) find a high percentage of contemporaneous association between the Latin American equity market

[†] *CRS Report for Congress May 11, 2004*

and the US market. Moreover, they find that a high share of trade with the US has a strong positive impact on equity market comovements. Forbes and Chinn (2004) show that direct trade flows are the most important determinants of cross-country linkages. Chen and Zhang (1997) study the relationship between bilateral trade and cross-country return correlations and find that countries with more trade to a region tend to have higher return correlations with that region. Since Latin America is the fastest growing regional trade area with the US, especially during 1992 to 2003, we would expect a higher degree of comovement between the US and Latin American equity market returns during this period.

In this study we are trying to find out whether there has been a structural change in the bivariate correlations between the US and Latin American equity returns during the period spanning from 1988 to 2004. Specifically, we will answer the questions: Has any structural change happened to the degree of comovement among North and Latin American equity markets? If so, when did the change occur and how long was the transition period? In addition, having identified the transitions in the conditional correlation series we are investigating, our study will test whether these transitions coincide with liberalization episodes. Results from this test will add to previous studies that have questioned the success of liberalization. For example, Bekaert and Harvey (1995) find that some countries like Mexico and Chile became less integrated after the first two to three years of liberalization.

For this purpose we follow a two-step approach. The first step applies the dynamic conditional correlation model (DCC) proposed by Engle (2002) to model the fluctuations of correlation and volatility between each Latin American stock market with that of US over time. In the second step a smooth transition analysis is applied to the bivariate conditional correlations estimated in the first step. Smooth transition analysis is an approach to modeling deterministic structural change in a time series regression. So our setup allows us not only to endogenously determine the date of change, but also whether the transition to the new regime was abrupt or gradual.

The remaining paper is divided into four sections. Section 2 presents methodology. Section 3 describes the data and presents summary statistics. Section 4 analyzes the results. Section 5 concludes.

2. Econometric Methodology:

In this part of the paper we follow a two-step approach. The first step applies the dynamic conditional correlation model (DCC) proposed by Engle (2002) to model the fluctuations of correlation and volatility between each Latin American stock market with that of US over time. In the second step we examine whether there has been any structural break. This is achieved by testing for stationarity in correlations. If a bivariate conditional correlation is stationary then a smooth transition process is not suggested, because no transition of any sort is apparent. On the other hand if a bivariate correlation series is nonstationary, a smooth transition model will be applied. This model will allow us to measure exactly when structural change occurs and how quickly it occurs.

2-1. Dynamic Conditional Correlation model:

I start this section by discussing a number of properties of asset return volatility and correlation that are observed empirically. These properties can indicate which techniques are appropriate to model volatility (which will be done in the first step of the methodology). They can also indicate why a DCC-GARCH model is appropriate to model equity market comovements. For asset return volatility, it is observed that large (small) changes in returns in one period tend to be followed by large (small) changes in subsequent periods. This is called volatility clustering which becomes more apparent as the frequency of the data increases. The GARCH class models have proven to be successful in capturing volatility clustering. It is also observed that volatility of asset returns often reacts differently to positive news than to negative news, and many studies document that negative shocks on asset prices tend to have a larger impact on volatility than do positive shocks of the same magnitude (see for example, Black (1976), Christie (1982) and Campbell and Hentschell, (1992)).

A number of studies have concluded that international correlations are not constant over time (see for example, Longin and Solnik (1995), Tse (2000), Engle and Sheppard (2001), Goetzmann *et al.* (2003) and Berben and Jansen (2005)). For example, Goetzmann *et al.* (2003) examine the correlation structure of world equity markets for a period of 150 years and find that international equity correlations change significantly over time, with peaks in the late 19th Century, the Great Depression, and late 20th Century.

The above properties observed in asset return volatility and correlations suggest that a time varying conditional correlation model that allows for asymmetric dynamics in volatility is needed. For this reason the DCC-GARCH model of Engle (2002) that was recently extended by Sheppard (2002) to allow for asymmetric dynamics in correlation and variance is used. To represent Engle's (2002) DCC model for the purpose of this study, let $r_t = [r_{1t}, r_{2t}]'$ be a 2x1 vector containing the equity market returns series where:

$r_t \mid \Omega_{t-1} \sim N(0, H_t)$. $H_t \equiv \{h_{it}\}$ for $i = 1,2$ is the conditional variance-covariance matrix of the equity returns vector $r_t = [r_{1t}, r_{2t}]'$ and Ω_t is the information set that includes all information up to and including time t. The multivariate DCC-GARCH structure can be easily understood by first rewriting the conditional variance-covariance matrix as:

$$H_t = D_t R_t D_t \qquad (2)$$

where $D_t = diag(\sqrt{h_{1t}}, \sqrt{h_{2t}})$ is the 2x2 diagonal matrix of time-varying standard deviations from univariate GARCH models with $\sqrt{h_{it}}$ on the diagonal and R_t is the time-varying conditional correlation matrix. The DCC model is designed to allow for two-stage estimation of the conditional variance-covariance matrix H_t. In the first stage the univariate volatility models for each market will be estimated and the best one will be selected using the Akaikie Information Criterion (AIC) from a class of models that are capable of capturing the common properties of equity returns variance. The models include GARCH of Bollerslev (1986), EGARCH of Nelson (1991) and GJR-GARCH of Glosten *et al*. (1993). In the second stage market returns, transformed by their estimated standard deviations resulting from the first stage, are used to estimate the parameters of the conditional correlations. So, once the univariate volatility models for markets are estimated, the standardized residuals for each market $e_{it} = r_{it} / \sqrt{h_{it}}$ are used to estimate the dynamics of correlation. The dynamic conditional correlation matrix R_t is assumed to vary according to a GARCH-type process.

$$R_t = Q_t^{*-1} Q_t Q_t^{*-1} \qquad (3)$$

$$Q_t = (1 - a - b)\overline{Q} + a e_{t-1} e'_{t-1} + b Q_{t-1} \qquad (4)$$

where $\overline{Q}$ is the unconditional correlation matrix of the e 's. $Q_t^* = diag\left\{\sqrt{q_{ii,t}}\right\}$ is a diagonal matrix containing the square root of the diagonal elements of $Q_t = \{q_{ij}\}_t$ and Q_t is a positive matrix which guarantees that $R_t = Q_t^{*-1} Q_t Q_t^{*-1}$ is a correlation matrix with ones on the diagonal and every other element less than one in absolute value. The typical element r_{ijt} of R_t will be of the form $r_{ijt} = q_{ijt} / \sqrt{q_{iit} q_{jjt}}$. a and b are scalar parameters that capture the effect of previous shocks and previous dynamic correlations. These parameters are the same for all assets, which means that all assets react in the same way to news. As Engle's (2002) model does not allow for asymmetries, Sheppard (2002) modified the evolution equation to be:

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B - G'\overline{N}G) + A'e_{t-1}e'_{t-1}A + B'Q_{t-1}B + G'n_{t-1}n'_{t-1}G \quad (5)$$

where $A = \begin{pmatrix} A_{11} & 0 \\ 0 & A_{22} \end{pmatrix}$, $B = \begin{pmatrix} B_{11} & 0 \\ 0 & B_{22} \end{pmatrix}$, $G = \begin{pmatrix} G_{11} & 0 \\ 0 & G_{22} \end{pmatrix}$ are 2x2 diagonal matrices, $I[.]$ is an indicator function and $n_t = I[e_t < 0] \circ e_t$ (where $\circ$ denotes the Hadamard product, i.e. element-by-element multiplication). The matrix $\overline{N}$ equals $E[n_t n'_t]$ for $t = 1,\ldots,T$. In the estimation procedure $\overline{Q}$ and $\overline{N}$ are replaced with sample analogues $T^{-1}\sum_{t=1}^{T} e_t e'_t$ and $T^{-1}\sum_{t=1}^{T} n_t n'_t$ respectively. Four models can be retrieved from model (5) by imposing restrictions on the parameter matrices A, B and G in equation (5). (See also Engle (2002) and Cappiello *et al.* (2006)).

Model I: The standard DCC model. This model is given in equation (4) by the restrictions $A_{11} = A_{22} = \sqrt{a}$, $B_{11} = B_{22} = \sqrt{b}$, $G_{11} = G_{22} = 0$ where a and b are the corresponding parameters in equation (4). This model assumes that each asset has the same parameter which means that all assets react in the same way to news. Moreover, each asset reacts in the same way to positive and negative news.

Model II: The generalized symmetric DCC model. This model is given by the restrictions $A_{11} \neq A_{22}, B_{11} \neq B_{22}$, $G_{11} = G_{22} = 0$ and simplifies to:

$$Q_t = (\overline{Q} - A'\overline{Q}A - B'\overline{Q}B) + A'e_{t-1}e'_{t-1}A + B'Q_{t-1}B$$

This equation assumes that assets react differently to news ($A_{11} \neq A_{22}, B_{11} \neq B_{22}$). However, each asset reacts in the same way to positive and negative news ($G_{11} = G_{22} = 0$).

2-2. Smooth Transition modeling:

We use smooth transition model suggested by Granger and Terasvirta (1993) and Lin and Terasvirta (1994) to determine any structural change in the conditional correlation series. This model was applied by Leybourne *et al.* (1997), Leybourne and Mizen (1999) and more recently by Chelley-Steeley (2005) and Berben and Jansen (2005). Since equity market integration is likely to be a gradual process smooth transition models are good in measuring market integration since they allow for a smooth transition between two correlation regimes. The smooth transition model is applied to bivariate equity market dynamic conditional correlations, which have been derived using the DCC-GARCH model from above. We consider the following logistic smooth transition regression model[‡] for the conditional correlation time series $\hat{r}_{ij,t}$ calculated above.

$$\hat{r}_{ij,t} = a + b \ \ S_t(g,t) + e_t$$

where e_t is a zero mean stationary $I(0)$ process. The smooth transition between the two correlation regimes is controlled by the logistic function S_t (?, t) defined as:

$$S_t(g,t) = (1 + \exp(-g(t - tT)))^{-1}, \ g > 0$$

where T is the sample size. The parameter t determines the timing of the transition midpoint which is half of the move from regime one to regime two. The parameter g determines the speed of the transition between the two correlation regimes. The change between the two correlation regimes is gradual for small values of ? indicating a gradual movement toward market integration. However, the change between the two correlation regimes is abrupt for large values of ?. The model assumes that conditional correlations change from one stationary regime with mean a prior to integration to another stationary regime with mean a+ß. If ß>0 the conditional correlations move upward, whereas if ß<0 the conditional correlations move downward. Before applying the smooth transition we need to test for stationarity of the conditional correlation series. If the series are nonstationary a smooth transition model may be applied as this indicates that the series evolves over time. However, if the conditional correlation series are stationary the smooth transition cannot be applied because no structural change is apparent.

Since the model assumes that the residuals are stationary, it is important to test for stationarity of the residuals after estimating the smooth transition model.

[‡] *We also used smooth transition with trend* $\hat{r}_{ij,t} = a_1 + b_1 t + a_2 S_t(g,t) + b_2 t S_t(g,t) + e_t$ *but the one without trend gives a better fit to our conditional correlation series.*

3. Data description:

Our data on stock prices consist of the S&P500 Composite index for the U.S. and four Latin American Composite local indices for Argentina, Brazil, Chile and Mexico. We use weekly data spanning from December 30th, 1988 through March 26th, 2004.

Data are provided by Emerging Market Database (EMBD).

3-1. Descriptive Statistics:

Table 3.1 Summary statistics of weekly returns (defined as the log difference of the price)

	Argentina	Brazil	Chile	Mexico	USA
Mean	0.0118	0.0226	0.0034	0.0049	0.0017
Median	0.0068	0.0181	0.0018	0.0065	0.0033
Maximum	0.7056	0.3662	0.1043	0.1750	0.0749
Minimum	-0.3618	-0.6808	-0.0708	-0.1771	-0.1241
Std. Dev.	0.0761	0.0813	0.0237	0.0377	0.0217

The summary statistics of the data are given in Table 3.1. From Table 3.2 we find that the series for Argentina and Chile are positively skewed which indicates a long right fat tail. Also, we find that the series for Brazil, Mexico and US are negatively skewed. For all five countries these series have asymmetric distributions. The kurtosis of each of the series is higher compared to the normal distribution, which has a kurtosis of 3. This means that the empirical distribution has more weight in the tails and is thus leptokurtic.

Table 3.2: Test for normality

	Argentina	Brazil	Chile	Mexico	USA
Skewness	2.4290	-0.5407	0.4495	-0.2692	-0.4967
Kurtosis	19.5357	11.6412	4.6194	4.9079	5.9324
Jarque-Bera	9839.24	2512.22	113.64	130.18	317.54
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

We can test for normality of stock returns by using the Jarque-Bera (1987) test. Results from Table 3.2 show the Jarque-Bera test rejects the null hypothesis of normality for all series at the 5% level. If the normality assumption does not hold also for the standardized residuals then we need to estimate the parameters of the GARCH model using Quasi-Maximum Likelihood (QML) instead of Maximum Likelihood (ML) (see Bollerslev and Wooldridge (1992)).

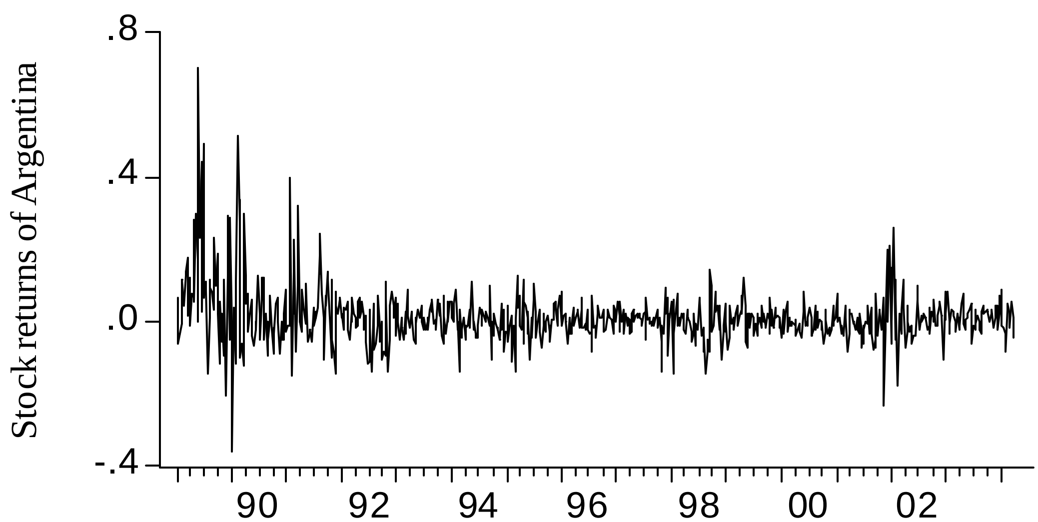

Figure 3.1: Weekly stock returns of Argentina by date

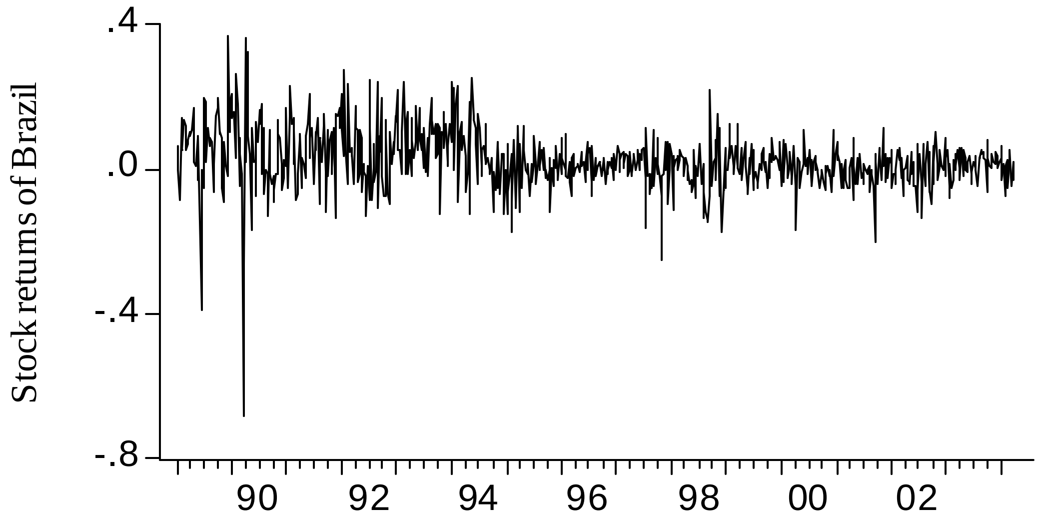

Figure 3.2: Weekly stock returns of Brazil by date

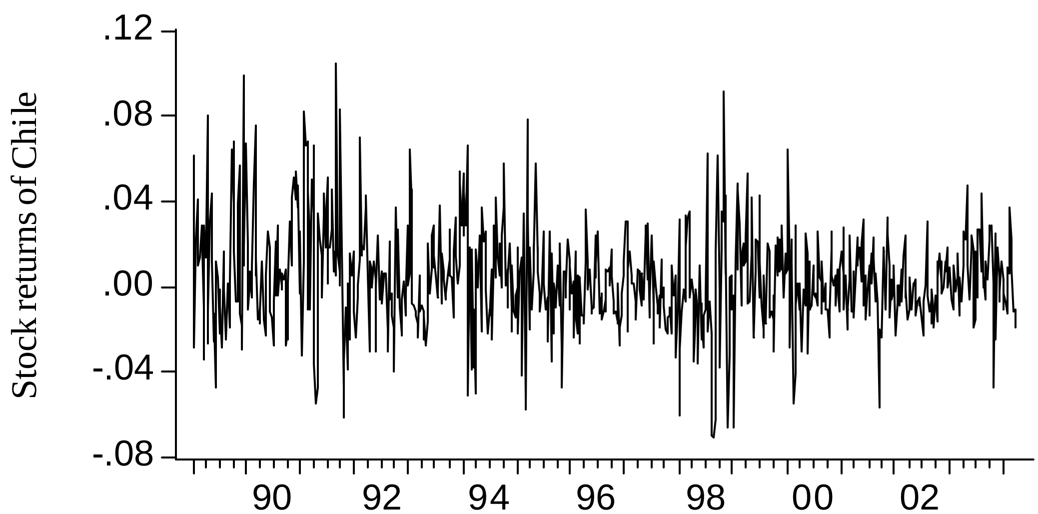

Figure 3.3: Weekly stock returns of Chile by date

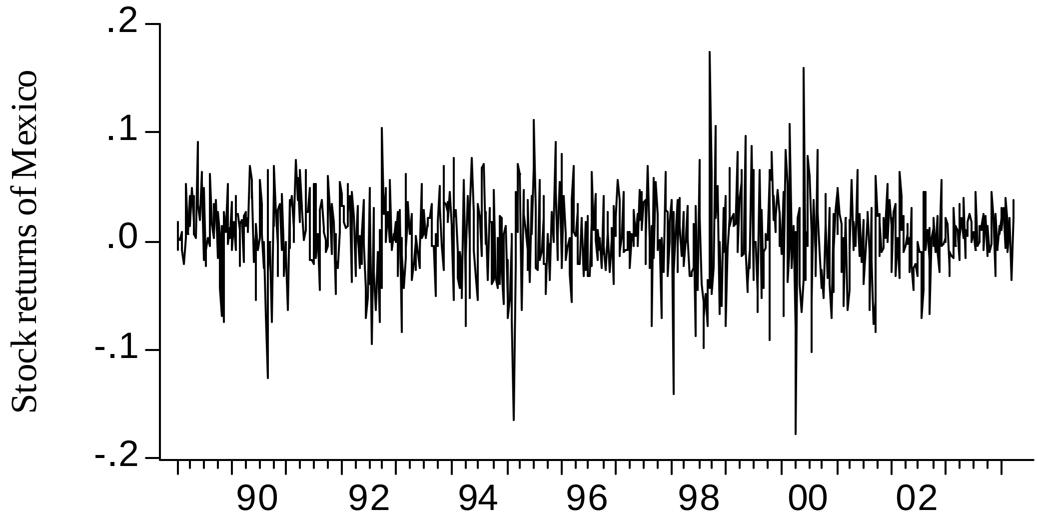

Figure 3.4: Weekly stock returns of Mexico by date

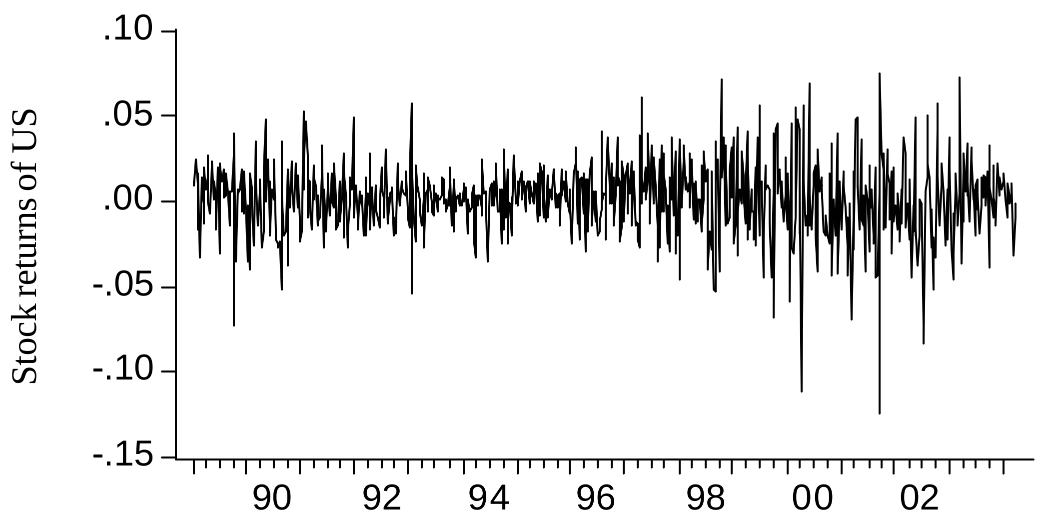

Figure 3.5: Weekly stock returns of US by date

In the figures above the weekly returns of the stock indices are plotted. We can see that there is volatility clustering.

Table 3.3: Test for autocorrelation of squared returns

	Argentina	Brazil	Chile	Mexico	USA
LjungBox(6)	277.50	103.62	115.66	31.98	62.88
Probability	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Table 3.3 shows Ljung-Box for up to 6 autocorrelation lags

The Ljung-Box autocorrelation test on the squared returns shows that series exhibit significant autocorrelation at the 1% level. This second order dependence of squared returns can be captured by a GARCH process.

Table 3.4: Unconditional correlations

	Argentina	Brazil	Chile	Mexico	USA
Argentina	1				
Brazil	0.2162	1			
Chile	0.2223	0.3128	1		
Mexico	0.2945	0.2758	0.2516	1	
USA	0.1792	0.2223	0.2273	0.4682	1

Table 3.4 gives the unconditional correlations between the five stock returns. We see that Mexico has the highest correlation with the US. This is probably due to the high trade share between the two countries. All these Latin American stock returns have positive correlation with the US stock return.

4. Empirical results:

4-1. Correlation Dynamics:

This section presents the empirical results of DCC models. In the first step the univariate GARCH model for each market is fitted and the best one selected using Akaikie Information Criteria. Table 3.5 contains the specification of the GARCH process selected by the AIC and the estimated parameters from these models. AIC information criteria shows that the equity market returns of Argentina, Brazil and Chile follow a GARCH(1,1) model which means there is no asymmetric effect in these markets. The equity market return of Mexico follows a GJR-GARCH (1,1) and the equity market return of U.S. follows EGARCH (1,1). We can see that the US and Mexican market returns contain significant asymmetry terms. For the US market return the asymmetry term is highly significant (1% level of significance). The Mexican market return is significant at the 5 % level.

Table 3.5: Univariate GARCH (1,1) models

	Model Selected	?	a	?	ß
Argentina	GARCH	0.000152***	0.2870***		0.7181***
Brazil	CARCH	6.35 e-05	0.1166***		0.8813***
Chile	GARCH	1.60 e-05*	0.1105***		0.8616***
Mexico	GJR-GARCH	6.45 e-05***	0.0515**	0.0874**	0.8594***
USA	EGARCH	-0.5597***	0.2096***	-0.1006***	0.9492***

*Notes: *, ** and *** indicate a significant at the 10, 5 and 1% levels, respectively.*

$$\textit{EGARCH model:}\ \log(h_t) = w + a\frac{|e_{t-1}|}{\sqrt{h_{t-1}}} + g\frac{e_{t-1}}{\sqrt{h_{t-1}}} + b\log(h_{t-1})$$

$$\textit{GARCH model:}\qquad h_t = w + a e_{t-1}^2 + b h_{t-1}$$

$$\textit{GJR-GARCH model:}\ h_t = w + a e_{t-1}^2 + g[e_{t-1} < 0]e_{t-1}^2 + b h_{t-1}$$

The tests of significance are computed with the robust standard errors of Bollerslev and Wooldridge (1992).

Table 3.6: Normality test for standardized residuals

	Argentina	Brazil	Chile	Mexico	USA
Skewness	0.3898	-0.7227	0.3527	-0.2375	-0.4635
Kurtosis	6.8054	6.01634	3.9148	3.7341	4.3699
Jarque-Bera	499.8191	370.5929	44.2023	25.3263	90.6334
Probability	<0.00001	<0.00001	<0.00001	<0.00001	<0.00001

The standardized residuals are still not normally distributed. Therefore, we must use Quasi-maximum likelihood and the corresponding standard errors are calculated. Using the standardized residuals from the first step, we continue with the second step of the estimation procedures for DCC models. Models I and II are estimated for the dynamics of conditional correlation among the US and the Latin American local indices returns. The estimation results of all the models are given in Table 3.7:

Table 3.7: DCC-GARCH Models

Model I			
a	*b*	*LLF*	
*0.0125****	*0.9543****	*7944.1*	
Model II			
	a	*b*	*LLF*
Argentina	*0.0082****	*0.9708****	*7944.8*
Brazil	*0.0464****	*0.9450****	
Chile	*0.0114****	*0.9875****	
Mexico	*0.0024****	*0.9780****	
USA	*0.0236****	*0.9637****	

*Notes: *, ** and *** indicate a significant at the 10, 5 and 1% levels, respectively.*

Two different models were estimated for the dynamics of the correlations. Model I was estimated allowing for no asymmetries in the correlation dynamics. In addition, each of the matrices, A and B, are diagonal with the same value on each diagonal. Model II was estimated allowing for no asymmetries in the correlation dynamics. In addition, each of the matrices, A and B, are diagonal with different values for each diagonal element. Results in Table 3.7 show that Model II slightly outperforms Model I since it has a higher log likelihood value.

4-2. Has any change happened to the correlations?

In order to answer this question we first need to plot all the conditional correlations that were estimated using the DCC model. An eyeball view of the graphs below clearly shows an increase in the average level of the conditional correlations, which is an indication that the level of integration between the US equity market and that of Argentina, Brazil, Chile and Mexico has increased.

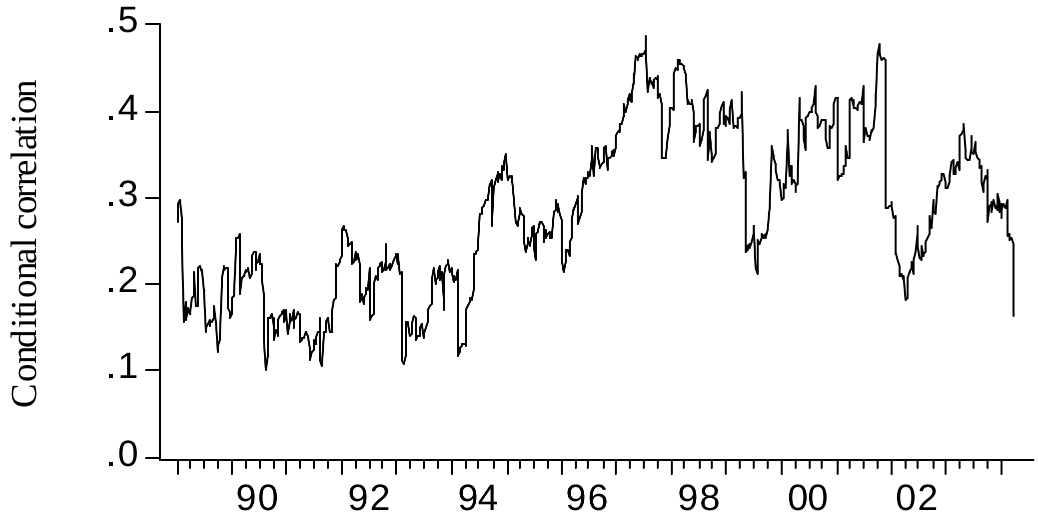

Figure 3.6: Conditional correlation between US and Argentinean equity returns

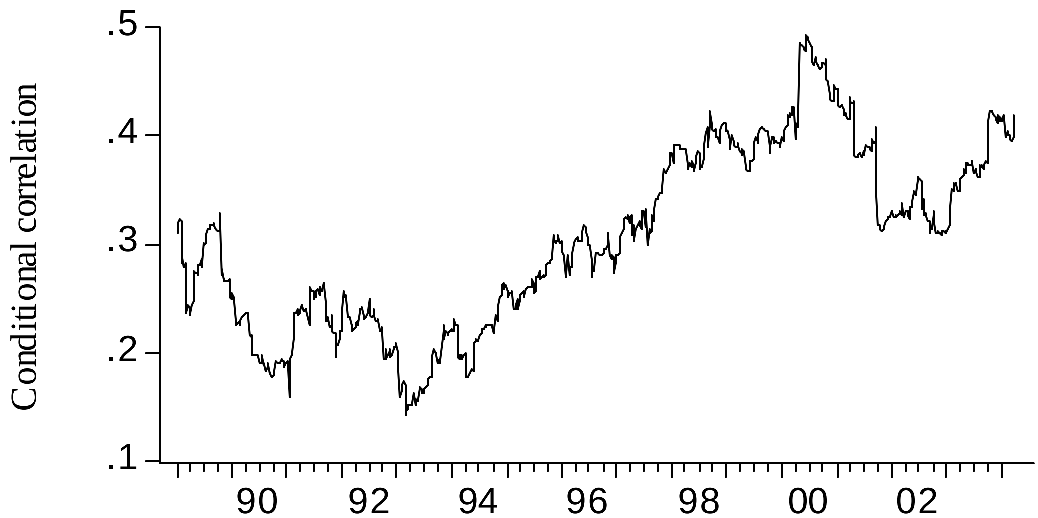

Figure 3.7: Conditional correlation between US and Brazilian equity returns

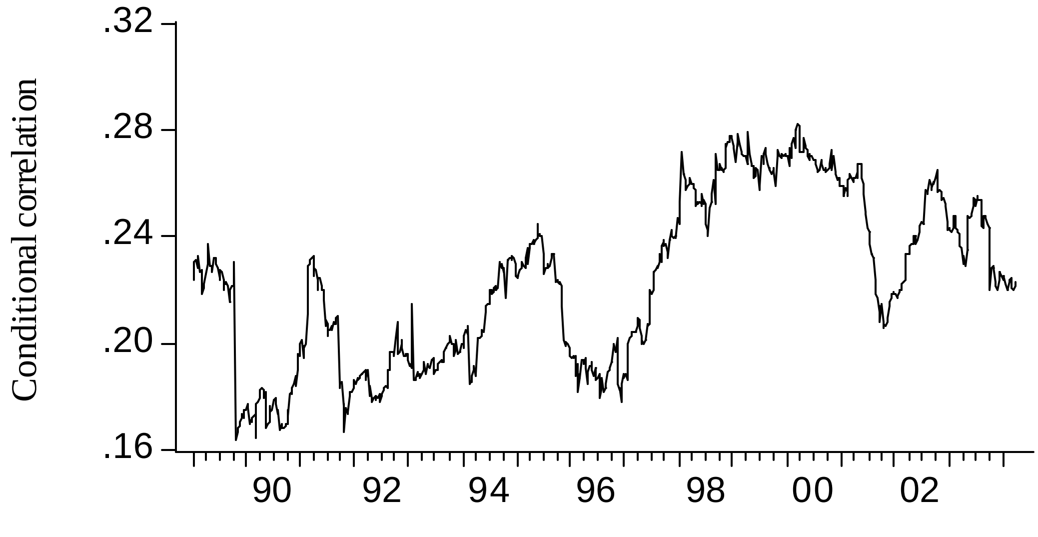

Figure 3.8: Conditional correlation between US and Chilean equity returns

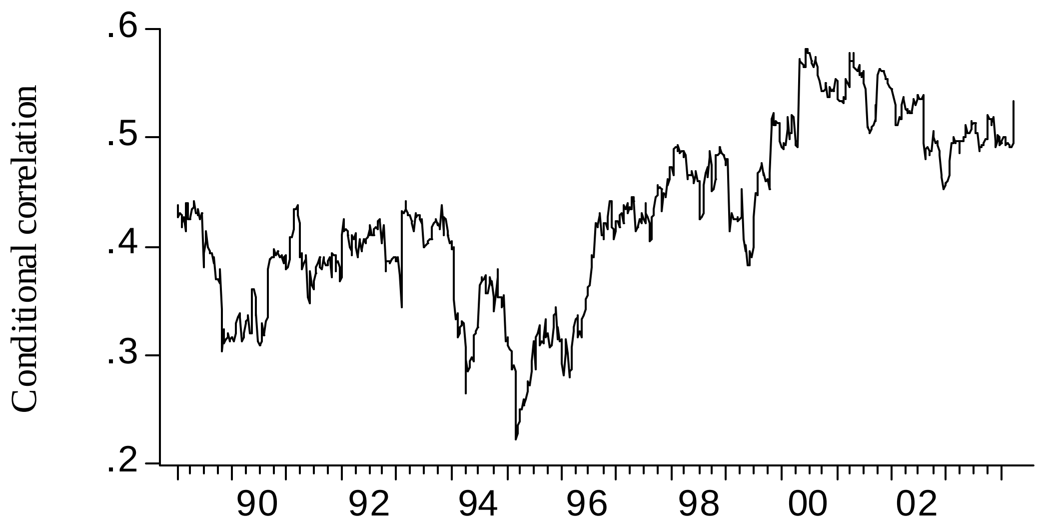

Figure 3.9: Conditional correlation between US and Mexican equity returns

Table 3.8 contains the computed ADF tests for conditional correlations between US and each of the Latin American markets. All the bivariate conditional correlations are found to be non-stationary at the 10% level. These ADF tests provide some information about bilateral integration. The non-stationarity of these conditional correlations means that the degree of bilateral co-movement between the US equity market and each of the Latin American equity markets may have changed.

Table 3.8: Computed augmented Dickey-Fuller statistics: prior to the fitting of the smooth transition model.

	Correlations in levels	*Correlations in first differences*
Argentina-USA	-3.132	*-29.18***
Brazil-USA	-2.805	*-14.01***
Chile-USA	-2.560	*-31.11***
Mexico-USA	-3.231	*-21.39***

*Notes: The ADF statistics have been computed with a constant and a trend. The optimal lag length is selected by Akaike information criterion. Significance at a 1% and 5% level is denoted by ** and * respectively.*

From Table 3.8 we conclude that all the conditional correlations are nonstationary in levels and stationary in the first differences, which means that the series are integrated of order one.

Table 3.9: Summary statistics of the bivariate conditional correlations

	Mean	*Min*	*Max*	*Std*
Argentina	*0.2812*	*0.1022*	*0.4869*	*0.093*
Brazil	*0.3051*	*0.1435*	*0.4927*	*0.083*
Chile	*0.2231*	*0.1638*	*0.2821*	*0.031*
Mexico	*0.4280*	*0.2223*	*0.5813*	*0.078*

In Table 3.9 we have computed the mean of the bivariate conditional correlations between the US and each of the respective Latin American markets as this will give us which market is highly integrated with the US one. On average Mexico has the highest conditional correlation with the US, approximately 43%, followed by Brazil at 30%, Argentina at 28% and Chile at 22%. This indicates that Mexico is highly integrated with the US compared to the other Latin American equity markets. This is not surprising since Mexico has engaged in a free trade agreement with the US since 1994.

4-3. When did the change occur?

Since we find that all the bivariate conditional correlations are non-stationary, we estimate the smooth transition model for all these series. Table 3.10 gives the results of the estimated smooth transition model. a and a+ß are the correlations in the old and new regime, respectively. If ß is greater than zero, there will be an upward movement in the correlations. However, if ß is less than zero there will be a downward movement in the correlations. ? determines the shape of the transition curve, while tT determines the middle of the transition period. The change between correlation regimes is abrupt for large values of ?.

Table 3.10: The estimated smooth transition model

	a	*ß*	*?*	*t*	*Adjusted R^2*
Argentina	*0.18331 (46.03)*	*0.16402 (32.60)*	*7.03185 (8.76)*	*0.399 (53.50)*	*0.6177*
Brazil	*0.22519 (96.18)*	*0.16276 (48.16)*	*6.21574 (12.92)*	*0.509 (93.81)*	*0.7818*
Chile	*0.20088 (217.91)*	*0.05114 (36.20)*	*35.29345 (3.52)*	*0.566 (185.55)*	*0.6320*
Mexico	*0.36864 (160.96)*	*0.14938 (36.85)*	*5.93267 (11.18)*	*0.6027 (81.16)*	*0.6921*

Note: t-statistics are given in brackets

The results from the estimation of the smooth transition model suggest an increase in market integration between the US and Latin American countries (Argentina, Brazil, Chile, Mexico) as ß > 0 for all these countries. Since ? is largest for Chile, the transition towards integration with the US is faster than that for Argentina, Brazil and Mexico. There is little difference between the transition midpoints of these countries. In the case of Argentina it is approximately in 01/1995, for Brazil it is approximately in 09/1996, for Chile it is approximately 07/1997, and for Mexico it is approximately 02/1998. The highest R^2 is for Brazil (78.18 %) suggesting that for this country the smooth transition model explains a greater proportion of the variation in conditional correlations than for any other country. The R^2 is approximately 62% for Argentina, 63% for Chile and 69% for Mexico.

The correlation between Argentina and the US increased from 0.1833 to 0.3473. The transition phase covers the period from 10/1989 to 11/1999. The beginning of the transition phase coincides with the beginning of the liberalization date 1989[§]. The correlation between Brazil and the US increased from 0.2252 to 0.3879. The transition phase covers the period from 3/1991 to 1/2002. The beginning of the transition phase coincides with the liberalization date for Brazil which is 1991. The correlation between Chile and the US increased slightly from 0.2009 to 0.2520. The transition phase covers the period from 11/1996 to 6/1998. The beginning of transition phase does not coincide with the beginning of liberalization date 1992, but the transition period is within the high bilateral period 1992-2003. Finally, the correlation between Mexico and the US increased from 0.3686 to 0.5180. The transition phase covers the period from 1/1991 to 11/2003. The beginning of the transition period does not coincide with the beginning of the liberalization date 1989, but most of the transition period falls within the high bilateral trade period 1992-2003.

[§] *The date of the beginning of each liberalization episodes is obtained from BeKaert, Harvey and Lundblad (2001, Table 1).*

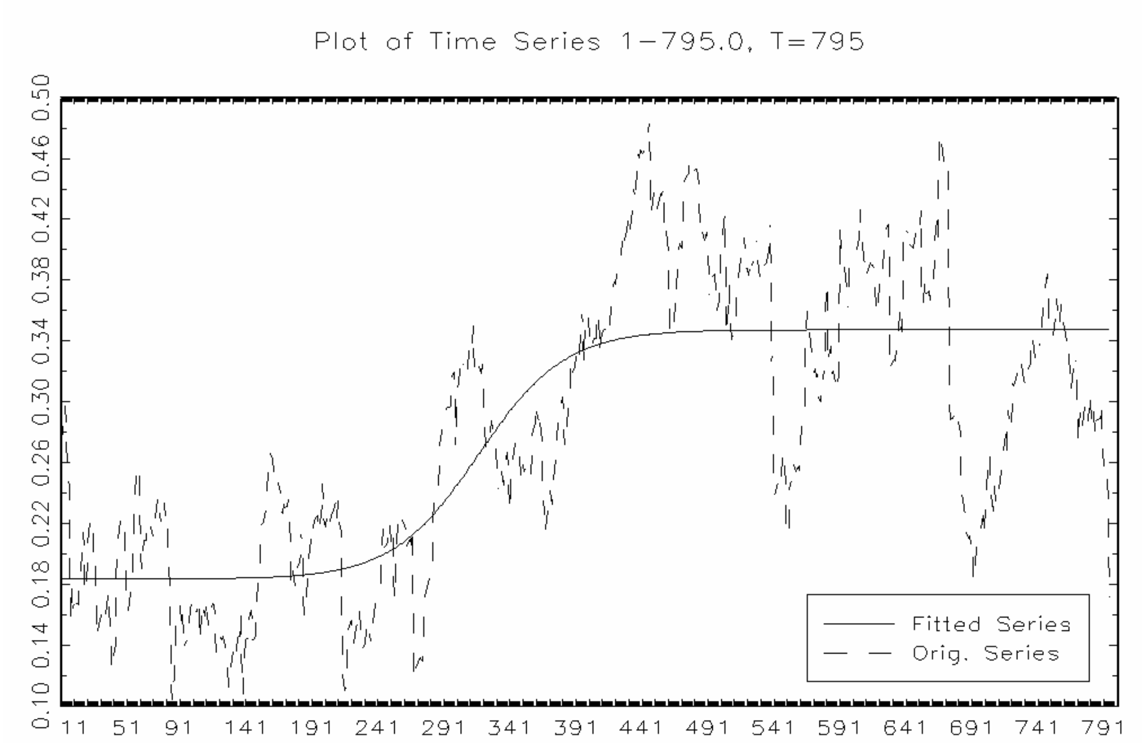

Figure 3.10: Plots the fitted series and DCC correlation between US and Argentina.

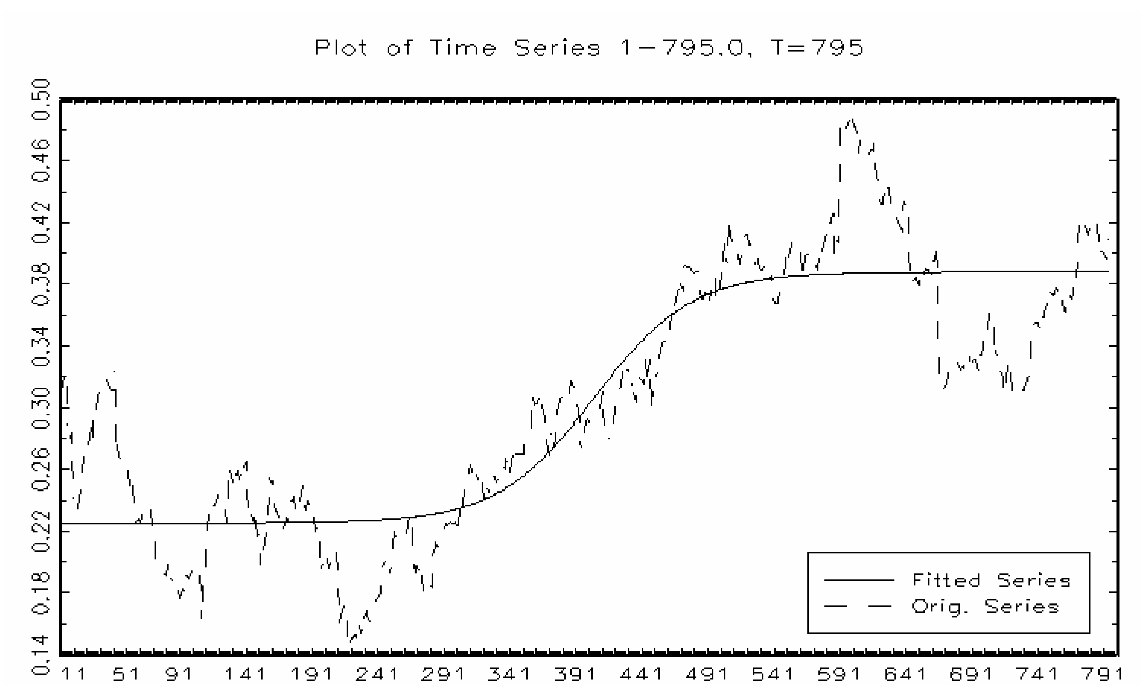

Figure 3.11: Plots the fitted series and DCC correlation between US and Brazil.

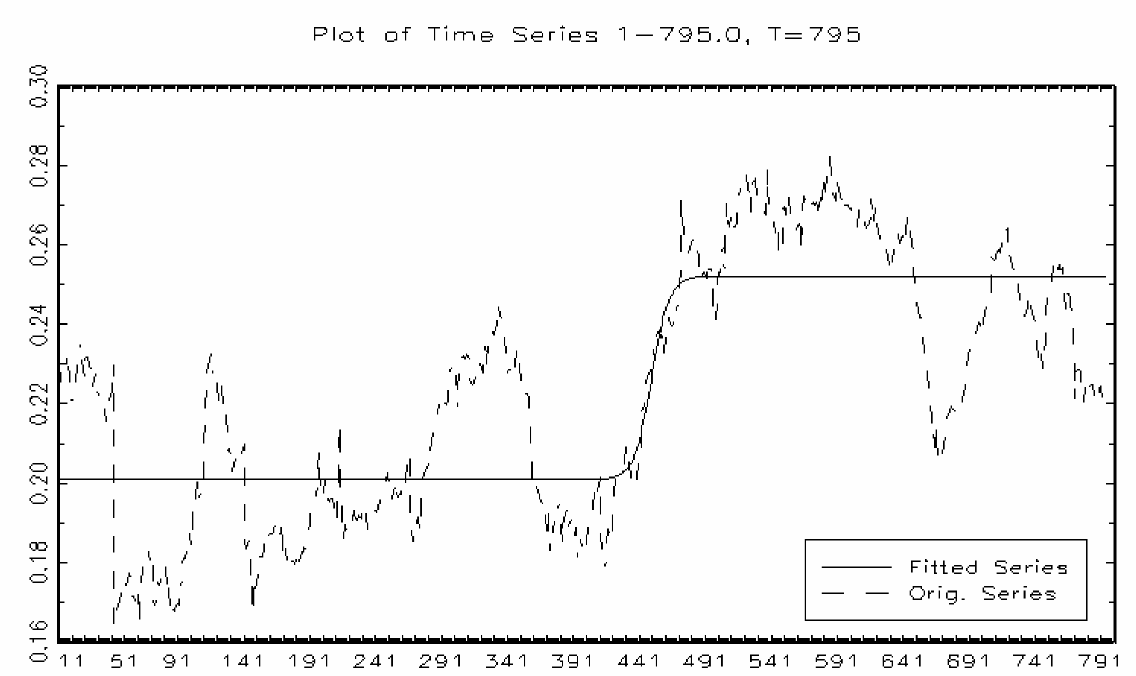

Figure 3.12: Plots the fitted series and DCC correlation between US and Chile.

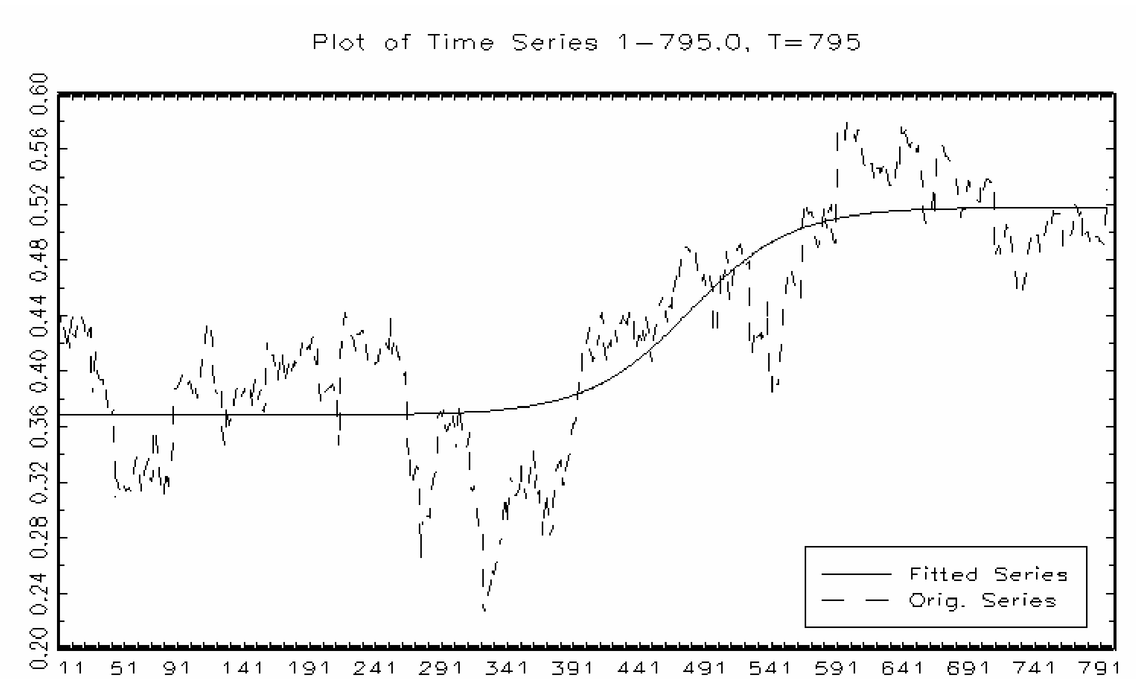

Figure 3.13: Plots the fitted series and DCC correlation between US and Mexico.

5. Conclusion:

The main objective of this paper is to examine whether the Latin American equity markets of Argentina, Brazil, Chile and Mexico have become more integrated with the US equity market. We have used several methods including DCC multivariate GARCH and a smooth transition model. Results show an increase in the degree of market integration between these countries and the United States. Moreover, we find that the beginning of rapid integration coincides with the beginning of liberalization for Argentina and Brazil. For Mexico and Chile we find that the period of rapid integration is within the period of increasing bilateral trade. The implication of our study for investors is that optimal portfolios have changed as a result of the correlation shifts. Except for Chile the conditional correlations between United States and other Latin American equity returns have significantly increased which may lessen the advantages of portfolio diversification between the US and these countries. Although Chile has the lowest correlation with the United States, it has the highest ? which means the degree of integration is moving faster than that of any other Latin American equity market. For policy makers, an increase in the level of correlations between US and these Latin American equity markets means that equity market disturbances in US are more likely to be transmitted to these countries, which may have adverse consequences for the stability of the financial system. One extension of this paper is to investigate the economic factors behind the shift in the correlations and see whether there are some differences between these Latin American countries.

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