The Interaction between Latin American Stock Markets and the US

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Abstract

This paper investigates the linkages between the Latin American stock markets and the US over the period January 1988 to December 1999. Both short run fluctuations and long run relationships are modelled. Results show that there are strong interrelationships between the Latin American markets and that the US exerts an influence on most countries. There exists a long run equilibrium but it has only a weak impact on the relationships. All linear regressions exhibit nonlinearity. Smooth transition models are used to account for nonlinearity. Findings suggest that this nonlinearity is captured through either structural breaks around crisis dates or US stock returns. Results show that US stock returns have a significant impact on all Latin American markets. Importantly, once nonlinearity is accounted for, the impact of the long run equilibrium is more significant.

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1 Introduction

The recent past has borne witness to turbulent times in world capital markets. Over the 1990s there was wide spread growth particularly in emerging equity markets. Many countries had adopted policies of liberalisation towards the end of the 1980s and subsequently liquidity in emerging equity markets increased rapidly in the 1990s. This growth has been tempered by financial crises such as the 'tequila' crisis, the Asian financial crisis, Russian crisis, and the subsequent events in Latin America.

Over recent years interest has focussed on linkages between asset markets in developed economies and emerging markets. The level of interaction or interdependence between markets has important consequences in terms of predictability, portfolio diversification and asset allocation. Theory predicts that gains can be achieved through international portfolio diversification if returns in the different markets are not perfectly correlated. Policies of deregulation in and the liberalisation of capital markets, coupled with technological advances, suggests that markets have become more integrated over time. Increasing levels of integration suggests that opportunities for portfolio diversification are reduced. Moreover, evidence from crisis events suggests that market co-movements lead to contagion.

Evidence of spillover and volatility transmission from one market to another is well established (see, *inter alia*, Engle *et al.* (1990) and Hamao *et al.* (1990)). Further evidence on contagion and financial crises highlights the impact of events such as the Asian crisis and the Russian crisis on other markets across the globe (see, *inter alia*, Kaminsky and Reinhart (1998), Edwards and Susmel (2001) and Bae *et al.* (2003)). In addition to these short run relationships, there is a body of evidence suggesting capital markets share common trends over the long term (Kasa (1992) and Choudhry (1997)). This suggests that for investors with longer term investment horizons, the benefits of international portfolio diversification could be overstated. However, despite the existence of such long run relationships it is unlikely that the benefits of diversification will be eroded since returns may only react very slowly to the trend.

While the evidence on asset market linkages between emerging economies is growing, few studies explicitly account for time variation in these relationships. We allow for such variation by considering regime switching in the form of smooth transition models. This will establish whether the relationship between asset markets is nonlinear and capture any variation within the relationship. The use of such models allows for the possibility of a smooth transition between regimes in contrast to threshold regressions and Markov switching models that assume abrupt changes between regimes.

We investigate the both the short term interactions and the long run linkages between six Latin American stock markets (Argentina, Brazil, Chile, Columbia, Mexico and Venezuela) and the US. These linear relationships are tested for smooth transition linearity using a range of candidate transition variables. These are individual country stock returns, US stock returns, the returns on a Latin American regional index[1] and time. Using US stock returns as a nonlinear transition variable allows for time variation in these relationships as market conditions in the US change. Individual country returns capture domestic influences while the Latin American returns suggests regional are the most significant cause of time variation. Time captures the impact of a possible structural break in the sample period.

We find that US stock returns have a significant impact on stock returns in most Latin American countries. There are a number of different short term interrelationships between the Latin American markets and although there is a long run equilibrium relationship between the markets and the US, it is not significant in all economies. All the estimated linear regressions exhibit evidence of nonlinearity.

The most significant transition variable for the majority of the markets is US stock returns followed by time. Using smooth transition regression models with US stock returns as the transition variable we uncover significant changes from the estimated linear relationships. In particular, there is clear evidence that the majority of the markets faced a three/four year period of stability over the mid 1990s.

Structural breaks are estimated to provide the strongest nonlinear influence in Argentina, Mexico and Columbia. The break dates coincide with the period of hyperinflation in Argentina in 1989, the Mexican peso crisis in late 1994, and the consequences of the Russian crisis in 1998 impacting upon Latin American markets.

[1] The index is constructed by weighting each of the six constituents by market capitalisation.

The remainder of the paper is organised as follows. Next, we briefly review the existing literature investigating asset market linkages in emerging markets and specifically Latin America. In section three, we discuss the methodology while section four presents the results and analysis. Section five offers some concluding remarks.

2 Literature Review

Research into asset market linkages and integration in both developed markets and emerging markets has developed over recent years establishing the nature of these relationships for different assets and markets. While the majority of studies have focussed on on emerging equity markets in the Pacific Basin (see, *inter alia*, Phylaktis and Ravazzolo (2002) and Manning (2002)), there is evidence on for other asset markets (for example, Phylaktis (1999) using real interest rates) and other emerging economies (for example, Bekaert and Harvey (1995, 1997)).

It is well understood that markets, developed and emerging, can move together over the short run. Engle *et al.* (1990) and Hamao *et al.* (1990) provide evidence that volatility spillovers occur between asset markets suggesting that events in one market can be transmitted to others. More recent studies of financial crises and contagion suggest that there is significant transmission across markets. For example, Kaminsky and Reinhart (1998), Edwards and Susmel (2001) and Bae *et al.* (2003) provide evidence that events such as Asian crisis and the Russian crisis have significant knock-on effects for markets in Latin America.

However, there is strong evidence to suggest that markets display common trends over the long term. A number of studies have established the existence of a long run equilibrium relationship between Latin American stock markets and between these markets and the US (see, *inter alia*, Choudhry (1997), Garrett and Spyrou (1999), and Chen *et al.* (2002)). Recently studies have investigated the stability of this long run relationship (see Fernández-Serrano and Sosvilla-Rivero (2003) and Yang *et al.* (2004)).

Over the past twenty years, Latin American countries have under gone a process of financial liberalisation. Most economies have adopted deregulation and privatisation policies and have entered into trade alliances such as

MERCOSUR. The implication of such policies and the development of trade alliances is that they strengthen policy coordination and economic ties between economies. Along with the growing influence of multinational companies and rapid developments in information and communications technology, these factors contribute to the sense of greater integration between markets.

The evidence of cointegrating relationships between Latin American stock markets and between these markets and the US implies that over the long term fewer opportunities for diversification are available to investors. Evidence of integration between the Latin American economies indicates that investors wishing to diversify their portfolios by including Latin American stocks need not invest in all markets. However, cointegration with developed markets such as the US, suggests that the benefits to international diversification in these markets may be removed in the long run. The existence of common trends between markets is not sufficient to eradicate the benefits of portfolio diversification. Garrett and Spyrou (1999) highlight that stock markets may not react strongly to such trends with little impact on the benefits to diversification.

Few studies have investigated how the interrelationships between emerging markets and developed markets evolve over time. Bekaert and Harvey (1995, 1997) provide evidence on time-varying integration between emerging markets and the world market. While Edwards and Susmel (2001) use SWARCH models to investigate volatility co-movements between Latin American equity markets. This time variation has important consequences for investors considering international portfolio diversification.

Recent empirical evidence shows that correlations are higher during bear markets than bull markets, see Longin and Solnik (2001), so interdependencies between equity markets change according to the state/regime of the market. Ang and Bekaert (2002) show that the asymmetric GARCH is unable to take account of this type of correlation pattern. Hence it is the regime or the nonlinearity that is important rather than the changing volatility. Further evidence has shown that regime switching models that account for different phases in the business cycle are quite successful in this regard, see Ang and Bekaert (2002), Perez-Quiros and Timmermann (2000), Guidolin and Timmermann (2003).

A special class of regime switching models, where the state variable is observed, that also allows intermediate positions between the regimes is the smooth transition models, see van Dijk *et al.* (2002). This is seen as an appropriate regime switching approach if we want to examine the nature of the underlying regime and have proven to work well with specifications of two or more explanatory variables.

Sarantis (2001) investigates potential nonlinearities and cyclical behaviour in the stock prices of the G7 economies using smooth transition autoregressive regressions (STAR). He demonstrates that stock prices exhibit nonlinearity in all seven markets and that the slope parameters imply slow rather than abrupt transitions. Evidence also shows that the estimated STAR models provide superior out of sample forecasts to the linear specifications.

3 Methodology

In order to evaluate the dynamic interdependence between the Latin American stock markets we test for cointegration amongst the markets using the Johansen technique (see Johansen (1988) and Johansen and Juselius (1990)) to establish any long term common trends and then estimate a VECM to capture the short run dynamics.

$$y_t = \mu + A_1 y_{t-1} + \ldots + A_k y_{t-k} + \varepsilon_t \tag{1}$$

$$\Delta y_t = \mu + \Gamma_1 \Delta y_{t-1} + \ldots + \Gamma_{k-1} \Delta y_{t-k-1} + \Pi y_{t-k} + \varepsilon_t \tag{2}$$

The VECM is initially specified with a maximum lag order of 4 and then a general to specific search is undertaken to arrive at the most parsimonious ECM for each country. This is reported as the linear specification.

Each of the stock return equations within the VECM is tested for smooth transition type nonlinearity using the approach of Luukkonen *et al.* (1988).

$$x_t = \beta_0 + \sum_{j=1}^{p} \beta_{1j} x_{t-j} + \sum_{j=1}^{p} \beta_{2j} x_{t-j} s_{t-1} + \sum_{j=1}^{p} \beta_{3j} x_{t-j} s_{t-1}^2 + \sum_{j=1}^{p} \beta_{4j} x_{t-j} s_{t-1}^3 + \eta_t \tag{3}$$

where x_t includes the stock returns (Δy_t) and the error correction term, and s_{t-1} includes the candidate transition variables. An LM-type test can be adopted to test the null hypothesis, $H_0 : \beta_{2j} = \beta_{3j} = \beta_{4j} = 0, j = 1, \ldots, p$ against a general alternative:

$$LM = \frac{T(RSS_l - RSS)}{RSS_l}$$

where RSS_l is the sum of squared residuals from the linear equation and RSS is the sum of squared residuals from equation (3). The tests statistic is distributed as χ^2 with $3q$ degrees of freedom.

Given the recent finding that correlations among stock markets are influenced by the position on business cycle, we apply a regime switching model to each of the stock return regressions that exhibits nonlinearity. Specifically, a smooth transition regression (STR) model is adopted which allows for the possibility that the transition from one regime to another is smooth, see van Dijk *et al.* (2002) and Aslanidis *et al.* (2003). In the simplest case of two regimes, the model is given by:

$$\Delta y_t = \delta_0 + \sum_{i=1}^{p} \delta_i \Delta y_{t-i} + \Pi_1 y_{t-1} + \left[\theta_0 + \sum_{i=1}^{p} \theta_i \Delta y_{t-i} + \Pi_2 y_{t-1}\right] F(s_{t-1}) + \varepsilon_t \quad (4)$$

Alternatively, letting z_t be the dependent variable, i.e. the stock return for a given Latin American market, and w_t be a $(k+1) \times 1$ vector containing the explanatory variables, (i.e. a constant, lagged stock returns from the six Latin American markets and the US and the error correction term):

$$z_t = \alpha_0' w_t + F(s_{t-1}) \alpha_1' w_t + u_t \quad (5)$$

where α_0 and α_1 are the coefficient vectors, u_t is the error term, which is $iid(0, \sigma^2)$, $F(s_{t-1})$ is the transition function defining the regime and s_{t-1} is the transition variable. The role of the explanatory variables in w_t can differ between the two regimes through the coefficients α_1. For any given value of $F(s_{t-1})$, the STR model of equation (5) is linear with coefficient vectors of α_0 and $\alpha_0 + \alpha_1$ at the extremes of $F(s_{t-1}) = 0$ and $F(s_{t-1}) = 1$ respectively. The transition function is assumed to follow either a logistic function (LSTR):

$$F(s_{t-1}) = \{1 + exp[-\gamma(s_{t-1} - c)]\}^{-1} \qquad \text{where} \quad \gamma > 0 \tag{6}$$

or an exponential function (ESTR):

$$F(s_{t-1}) = \{1 - exp[-\gamma(s_{t-1} - c)^2]\} \qquad \text{where} \quad \gamma > 0 \tag{7}$$

We estimate the performance of both types of function for each of the six markets. A number of studies that have applied these type of approaches to modelling stock returns have advocated the use of the logistic as opposed to the exponential function (for example see Aslanidis *et al.* (2003) and Sarantis (2001)). The S-shaped logistic function is more intuitive to bull and bear stock market regimes or recessions versus expansions, as opposed to the U-shaped exponential function which cannot be used to identify expansion or contraction behaviour. For the logistic function the process documents the change from a lower (contractionary) regime to an upper (expansionary) regime. With the exponential function the switch is from an outer regime to a middle regime.

The transition function determines the regime and is itself governed by the transition variable, s_{t-1}, and by the speed of transition, γ. As $\gamma \to \infty$ the transition becomes more and more abrupt, $F(s_{t-1})$ becomes a step function and the model approaches the standard threshold regression model. The transition function is bounded by zero and unity, which is determined by s_{t-1}. The parameter c is the threshold variable and the transition function is dependent on the position of the transition variable relative to the threshold variable. For example, when $s_{t-1} = c$, $F(s_{t-1}) = 0.5$ for the logistic function and $F(s_{t-1}) = 0.0$ for the exponential function.

The modelling procedure to determine the appropriate transition variable is as follows:

First, we undertake a 2 dimensional grid search of the residual sum of squares (RSS) over values of γ and c in order to identify the appropriate transition variable, i.e. the variable which minimises the RSS.[2] We allow the transition variable s_{t-1} to be one of four candidate variables, the first lag of the country stock returns, the first lag of US stock returns, the returns on

[2]Each grid search involves $\gamma = 1, 2, \ldots, 200$ and 40 values of c.

the Latin American regional stock index at lag one and time. We consider time as a potential transition variable to allow for the possibility of structural change.

Next ordinary least squares estimates of the coefficient values are obtained as initial values of the model conditional on the choice of transition variable and the corresponding values of γ and c from the grid search.

The final model is estimated by non-linear least squares including estimation of the parameters γ and c. Estimation of the slope parameter, γ, can be problematic. Teräsvirta (1994) and others suggest that the transition function $F(s_{t-1})$ is standardised to make γ scale-free. This implies dividing the exponent in $F(s_{t-1})$ by the standard deviation of s_{t-1} for the LSTR model and by the variance of s_{t-1} for the ESTR model. Accurate estimation of the slope parameter relies on a large number of observations in the neighbourhood of c.

Diagnostic tests are used to check the validity of the estimated models. Specifically we employ tests to check the validity of the linear and STR models with respect to autocorrelation, ARCH and normality. Standard statistical measures of model specification such as R^2, the residual standard deviation, RSS and the Akaike (AIC) and Schwarz (SBC) information criteria.

The linear, LSTR and ESTR models are also evaluated by examining their out-of-sample forecasting performance using one-step ahead forecasts. In addition to conventional predictive error statistics such as the mean squared error (MSE), the median squared error (MedSE) and the mean absolute error (MAE), we also use a number of statistics to compare the forecasting performance of alternative models. We compute the three tests of Diebold and Mariano (1995), the asymptotic test, the sign test and the Wilcoxon signed-rank test, and the tests of Pesaran and Timmermann (1992).

4 Data and Empirical Results

The data employed in this study is monthly observations from 1988:01 to 2004:12 drawn from the emerging market indices constructed by the International Finance Corporation. The index includes the stock price plus any dividend payments. The six Latin American countries studied are Argentina, Brazil, Chile, Columbia, Mexico and Venezuela. For the US the Standard & Poor 500 Index is adopted. The Latin American regional index is calculated by weighting the six Latin American indices according to their market capitalisation. All of the indices are expressed in terms of US dollars. The models are estimated over the period 1988:01 to 1999:12, the period 2000:01 to 2004:12 is reserved for out-of -sample forecasting.

Stock returns for the six Latin American countries, the US and the regional index are plotted in figure 1. Interestingly groups of the countries show the impacts of financial crises over the sample period. Large negative stock returns are witnessed in 1989 and early 1990 in Argentina and in Brazil. This is the period of hyperinflation in Argentina and the adoption of anti-inflationary policies in Brazil (Aggarwal *et al.*, 1999). The impact of the devaluation of the Brazilian real and accompanying crisis in January 1999 is felt in all markets except Argentina. The impact of the 'tequila crisis' in late 1994 is only witnessed in Mexico, its country of origin.

The data was tested for the presence of unit roots, stock prices are found to be nonstationary, I(1), while stock returns are stationary, I(0). A single cointegrating vector is found to exist between the six Latin American stock prices and US stock prices.[3] The finding of a single cointegrating vector is inline with previous studies such as Garrett and Spyrou (1999) and Yang *et al.* (2004). Error correction models (ECM) are then estimated for stock returns in each of the six Latin American countries. The ECMs are initially estimated with a maximum lag order of 4. A more parsimonious ECM is obtained for each country following a general to specific testing procedure to eliminate insignificant variables. The results of the estimation of this final model is reported as the linear specification (column 2) in each of tables 2 - 7.

The linear models highlight the fact that the error correction term is not very significant. In fact it is only highly significant for Columbia. This suggests that although there is evidence of market integration between the Latin American markets and the US, this equilibrium does not exert significant influence on current returns so is unlikely to eradicate the benefits to portfolio diversification.

[3]Results of the unit root and cointegration tests not reported. Full results of the tests are available from the authors on request.

There are a large number of interrelationships between the markets. However while lagged Brazilian stock returns influence all country stock returns except Chile, Brazilian returns are themselves only influence by their own lagged values and lagged Argentinean returns while lagged Chilean stock returns only impact stock returns in Chile and Columbia. Significantly, US stock returns exert an influence on returns in four of the markets, Argentina, Chile, Columbia and Venezuela. Providing strong evidence of linkages between and predictability across the different markets.

With the exception of the model for Columbian stock returns, the residuals from all models exhibit significant ARCH effects. The linear models are then adopted as the null models in testing linearity against smooth transition type nonlinearity using the tests of Luukkonen *et al.* (1988) discussed in section 3. The test outcomes are reported in table 1. It can clearly be seen that all markets exhibit some nonlinearity.

Having established that the models exhibit nonlinearity with respect to one or more of the candidate transition variables. The grid search procedure is then performed to identify the most appropriate transition variable and the initial values of the slope of the transition function, γ, and the threshold parameter, c.[4] In terms of the LSTR models, US stock returns is identified as the transition variable for Columbia, Mexico and Venezuela. Country stock returns capture the nonlinearity for Brazil and Chile while Argentina demonstrates evidence of a structural break. For the ESTR specifications the nonlinearity is captured by US stock returns for Brazil, Chile and Venezuela while structural breaks are present in Argentina, Columbia and Mexico.

The results of the estimation of the LSTR and ESTR models are reported in columns 3 and 4 of tables 2 - 7. Plots of the transition functions against time and against the transition variable are presented in figures 2 - 7. The results show that once we account for the nonlinearity present in the stock return relationships, the real significance of the estimated cointegrating relation is uncovered. The error correction term is now significant in most of the estimated LSTR models. Importantly the magnitude of the speed of adjustment parameter increases in the less frequent regime. Thus the market returns more quickly towards the long run equilibrium in response to any deviations from this trend when it finds itself in the atypical regime.

[4]The results of the grid search are reported in table A1.

The regression results show evidence that linkages between the markets and the interrelationships are strengthened. When the infrequently observed regime occurs when $F(s_{t-1}) = 0$ then the coefficients α_0 can often be large in magnitude, implying large changes in stock returns in response to small changes in other markets. In the normal regime, $F(s_{t-1}) = 1$ the coefficients $\alpha_0 + \alpha_1$ are much smaller in magnitude. When $F(s_{t-1}) = 1$ captures the atypical regime the reverse is observed.

Evidence of such nonlinear relationships and predictability is of great importance for investors and portfolio diversification. The observed time variation in the linkages between each of the six Latin American markets and the US implies vastly different behaviour in the alternative regimes. Simple linear models fail to capture the real nature of the markets over time, leading to incorrect inference if adopted in the investment decision making process.

Estimates of the magnitude of the transition slope parameter, γ are typically very large suggesting that transitions are abrupt. With the exception of Venezuela, there are relatively few observations in the region of the estimated threshold value, so few, if any, sample points are observed on the slope. The threshold value is, when the transition variable is either lagged domestic stock returns or lagged US stock returns, typically either highly negative or positive. Thus, the LSTR model separates between behaviour in a normal regime and an extreme 'atypical' regime. Naturally, when the switch is governed by a structural break, behaviour alters before and after the key event. The events isolated by structural breaks are the period of hyperinflation and currency collapse in Argentina in 1989, the 'tequila' crisis in Mexico in 1994 and the impact of the Asian and Russian crises in Columbia in 1998. In general, the LSTR models show that switching between regimes seems confined to the periods of instability at the beginning and ends of the sample period, with very few switches occurring in the period between 1992 and 1997.

For all markets the nonlinear models show an improvement in model specification with respect to the evaluation statistics and diagnostic tests. For instance R^2 improve significantly for the nonlinear models and with the exception of Mexico, all ARCH effects present in the linear model are removed. Although the ESTR specifications perform slightly better in this respect, few of the individual coefficients are significant. The LSTR coefficients are typically significant. This suggests, as in Sarantis (2001), that the logistic function is more appropriate for modelling stock return behaviour than the exponential function.

5 Conclusion

In this paper we investigate the linkages and interrelationships between six Latin American stock markets (namely, Argentina, Brazil, Chile, Columbia, Mexico and Venezuela) and the US. Common with the previous literature we establish the existence of a common trend between these markets. We further establish significant linear linkages between and predictability across markets. While evidence of such short run and long term relationships in and between emerging equity markets has been documented elsewhere, significantly, the novel aspect of this study is that we investigate time variation in these relationships.

We allow for time variation via regime switching using smooth transition regression (STR) models. We consider both logistic and exponential transition functions which are able to capture different types of behaviour. The logistic function allows for behaviour to differ between a lower and upper regime around the threshold value while the exponential function enables behaviour to differ between large and small deviations from the threshold.

In terms of market integration and the erosion of benefits to portfolio diversification over the long term much emphasis is placed upon the significance of any cointegration relationship between the markets. The linear analysis shows that although there exists a single cointegrating relationship, it is rarely significant in the estimated error correction models. This implies that although there is integration between the markets the benefits of diversification are unlikely to be eroded. In contrast, the nonlinear analysis highlights the significance of the long run equilibrium. In particular, the LSTR models show that the speed of adjustment to equilibrium differs significantly between regimes.

Further, the findings show that there are a wide number of interrelationships between the six Latin American markets. The nature and impact of these linkages changes markedly between regimes. Significantly, US stock returns exert important influence over returns in all six Latin American markets either linearly or as the transition variable in the nonlinear models.

Importantly, the STR models pick up significant financial crises and events such as the effects of hyperinflation and currency collapse in Argentina, the 'tequila' crisis in Mexico, the impact of the Asian and Russian crises and subsequent knock on effects in Brazil and elsewhere. This suggests that such events spillover between markets supporting the findings of the contagion and crises literature (Kaminsky and Reinhart (1998), Edwards and Susmel (2001) and Bae *et al.* (2003)).

In the majority of the STR models the results show that once we account for the nonlinearity, the ARCH effects present in the linear model are removed. This suggests, in line with Longin and Solnik (2001) that it is possibly nonlinearities or regimes in returns which are important rather than volatility. The explanatory power of the STR models is much greater than that of the linear models.

This paper highlights the importance of time variation in the relationships between Latin American and US stock markets. The models indicate the existence of nonlinear linkages between and predictability across markets. Crucially, evidence suggests that the nature of these linkages is different in alternative regimes.

References

Ang, A. and G. Bekaert 2002, "International asset allocation with regime shifts", *Review of Financial Studies*, 15, 1137-1187.

Aggarwal, R., C. Inćan and R. Leal 1999, "Volatility in emerging stock markets", *Journal of Financial and Quantitative Analysis*, 34, 33-114.

Aslanidis, N., D.R. Osborn and M. Sensier 2003, "Explaining movements in UK stock prices: How important is the US market?", Centre for Growth and Business Cycles Research, University of Manchester.

Bae, K.-H., G.A. Karolyi and R.M. Stulz 2003, "A new approach to measuring financial contagion", *Review of Financial Studies*, 16, 717-763.

Bekaert, G. and C.R. Harvey 1995, "Time-varying world market integration", *Journal of Finance*, 50, 403-444.

Bekaert, G. and C.R. Harvey 1997, "Emerging equity market volatility", *Journal of Financial Economics*, 43, 29-77.

Chen, G.-M., M. Firth and O.M. Rui 2002, "Stock market linkages: Evidence from Latin America", *Journal of Banking and Finance*, 26, 1113-1141.

Choudhry, T. 1997, "Stochastic trends in stock prices: Evidence from Latin American markets", *Journal of Macroeconomics*, 19, 285-304.

Diebold, F.X. and R.S. Mariano 1995, "Computing predictive accuracy", *Journal of Business and Economic Statistics*, 13, 253-263.

Edwards, S. and R. Susmel 2001, "Volatility dependence and contagion in emerging equity markets", *Journal of Development Economics*, 66, 505-532.

Eitrheim, Ø. and T. Teräsvirta 1996, "Testing the adequacy of smooth transition autoregressive models" *Journal of Econometrics*, 74, 59-75.

Engle, R.F., T. Ito and W.-L. Lin 1990, "Meteor showers or heat waves? Heterskedastic intra-daily volatility in the foreign exchange market", *Econometrica*, 58, 525-542.

Fernández-Serrano, J.L. and S. Sosvilla-Rivero 2003, "Modelling the linkages between US and Latin American stock markets", *Applied Economics*, 35, 1423-1434.

Garrett, I. and S. Spyrou 1999, "Common stochastic trends in emerging equity markets", *The Manchester School*, 67, 649-660.

Guidolin, M. and A. Timmermann 2003, "Recursive modelling of nonlinear dynamics in UK stock returns", *The Manchester School*, 71, 381-395.

Hamao, Y., R. Masulis and V. Ng 1990, "Correlation in price changes and volatility across international stock markets", *Review of Financial Studies*, 3, 281-307.

Johansen, S. 1988, "Statistical analysis of cointegrating vectors", *Journal of Economic Dynamics and Control*, 12, 231-254.

Johansen, S. and K. Juselius 1990, "Maximum likelihood estimation and inference on cointegration with applications to the demand for money", *Oxford Bulletin of Economics and Statistics*, 52, 169-210.

Kasa, K. 1992, "Common stochastic trends in international stock markets", *Journal of Monetary Economics*, 29, 95-124.

Kaminsky, G.L. and C.M. Reinhart 1998, "Financial crises in Asia and Latin America", *American Economic Review*, 88, 444-448.

Longin, F. and B. Solnik 2001, "Extreme correlation and international equity markets", *Journal of Finance*, 56, 649-676.

Luukkonen, R., P. Saikkonen and T. Teräsvirta 1988, "Testing linearity against smooth transition autoregressive models", *Biometrika*, 75, 491-499.

Manning, N. 2002, "Common trends and convergence? South East Asian equity markets 1988-1999", *Journal of International Money and Finance*, 21, 183-202.

Perez-Quiros, G. and A. Timmermann 2000, "Firm size and cyclical variations in stock returns", *Journal of Finance*, 55, 1229-1262.

Pesaran, M.H. and A. Timmermann 1992, "A simple nonparametric test of predictive performance", *Journal of Business Economics and Statistics*, 10, 461-465.

Phylaktis, K. 1999, "Capital market integration in the Pacific Basin region: an impulse response analysis", *Journal of International Money and Finance*, 18, 267-287.

Phylaktis K. and F. Ravazzolo 2002, "Measuring financial and economic integration with equity prices in emerging markets", *Journal of Internal Money and Finance*, 21, 879-903.

Sarantis, N. 2001, "Nonlinearities, cyclical behaviour and predictability in stock markets: International evidence", *International Journal of Forecasting*, 17, 459-482.

Teräsvirta, T. 1994, "Specification, estimation and evaluation of smooth transition autoregressive models", *Journal of American Statistical Association*, 89, 208-218.

van Dijk, D., T. Teräsvirta and P.H. Franses 2002, "Smooth transition autoregressive models - a survey of recent developments", *Econometric Reviews*, 21, 1-47.

Yang, J., J.W. Kolari and P.W. Sutanto 2004, "On the stability of long-run relationships between emerging and US stock markets", *Journal of Multinational Financial Management*, 14, 233-248.

Transition Variable	Argentina	Brazil	Chile	Columbia	Mexico	Venezuela
R_{t-1}	<0.0001	0.2526	<0.0001	<0.0001	0.0445	0.0270
R^{us}_{t-1}	0.1311	0.0170	0.0003	<0.0001	0.4503	<0.0001
R^{la}_{t-1}	0.2213	0.5464	<0.0001	<0.0001	0.1089	0.1030
$Time$	0.0100	0.6280	0.0001	<0.0001	0.4447	0.4837

Table 1 : Tests for STR nonlinearity

Variable	Linear	LSTR	ESTR
Constant	0.0200 (1.3038)	-0.0242 (-0.5088)	0.0300 (1.0093)
R^{ar}_{t-1}	-0.3120 (-1.8768)***	-1.0620 (-6.2575)*	-1.5079 (-1.9580)***
R^{ar}_{t-2}	-0.2485 (-1.8004)***	-0.7215 (-4.5078)*	-1.0222 (-2.3706)*
R^{co}_{t-3}	-0.2001 (-2.2568)**	-6.2478 (-3.1326)*	-12.8374 (-1.3524)
R^{us}_{t-4}	0.7496 (1.7611)***	4.0044 (2.8426)*	4.8384 (0.6037)
ect_{t-1}	-0.1201 (-1.7519)***	-0.7456 (-5.4239)*	-0.7279 (-1.2649)
$F()$		0.0379 (0.7563)	-0.0290 (-0.9694)
$F() \times R^{ar}_{t-1}$		1.0511 (5.3633)*	1.5108 (1.8838)***
$F() \times R^{ar}_{t-2}$		0.6654 (3.6254)*	0.9870 (2.2048)**
$F() \times R^{co}_{t-3}$		6.1361 (3.0722)*	12.7315 (1.3402)
$F() \times R^{us}_{t-4}$		-3.9762 (-2.7336)*	-4.7977 (-0.5949)
$F() \times ect_{t-1}$		0.7391 (5.0788)*	0.7251 (1.2469)
γ		201.5690 (0.4302)	186.1270 (2.3081)**
c		16.6758 (19.6042)*	13.4281 (20.5249)*
σ	0.1905	0.1575	0.1475
AIC	-3.2739	-3.6006	-3.7319
SBC	-3.3602	-3.3051	-3.4363
R^2	0.1308	0.4412	0.5099
RSS	0.0347	0.0223	0.0196
Diagnostic Test			
Autocorrelation	0.1630	0.6084	0.5491
ARCH	0.0339	0.9442	0.9743
Normality	<0.0001	<0.0001	<0.0001

Table 2 : Argentina
Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

Variable	Linear	LSTR	ESTR
Constant	0.0049 (0.0049)	-0.0668 (-0.6812)	-13.3297 (-1.2871)
R^{br}_{t-1}	0.0103 (0.1081)	-1.1030 (-5.1506)*	-57.7516 (-1.3186)
R^{br}_{t-3}	-0.1130 (-1.3529)	-1.3816 (-4.1335)*	-1.8584 (-0.7929)
R^{ar}_{t-4}	0.2039 (3.3095)*	-0.7152 (-2.6415)*	-0.0472 (-0.0361)
ect_{t-1}	0.0342 (0.4437)	-0.9234 (-5.9304)*	-0.3069 (-0.3069)
$F()$		0.0655 (0.6600)	13.3426 (1.2882)
$F() \times R^{br}_{t-1}$		1.3143 (5.2763)*	57.7724 (1.3194)
$F() \times R^{br}_{t-3}$		1.3387 (3.8365)*	1.7918 (0.7555)
$F() \times R^{ar}_{t-4}$		0.9400 (3.3712)*	0.2702 (0.2074)
$F() \times ect_{t-1}$		1.0427 (6.4405)*	0.4050 (0.2183)
γ		8102.58 (0.0024)	50.6122 (2.0074)**
c		-0.1799 (-1.4792)	-0.2232 (-31.9807)*
σ	0.1924	0.1709	0.1641
AIC	-3.2615	-3.4508	-3.5326
SBC	-3.3335	-3.1975	-3.2792
R^2	0.0599	0.2966	0.3518
RSS	0.0357	0.0267	0.0246
Diagnostic Test			
Autocorrelation	0.3879	0.6496	0.8783
ARCH	0.0395	0.9993	0.9989
Normality	<0.0001	<0.0001	<0.0001

Table 3 : Brazil
Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

Variable	Linear	LSTR	ESTR
Constant	0.0217 (3.3481)*	0.1531 (0.3906)	1.1674 (0.2953)
R^{ch}_{t-2}	-0.2568 (-2.1786)**	-9.9019 (-1.4322)	-25.6012 (-0.9418)
R^{co}_{t-1}	-0.1297 (-2.3314)**	1.5223 (1.4674)	23.0130 (1.1780)
R^{mx}_{t-1}	0.0896 (1.2957)	3.4147 (0.6708)	-31.8045 (-1.1992)
R^{mx}_{t-4}	-0.1941 (-2.0608)**	0.8056 (0.5121)	43.1470 (1.0397)
R^{ve}_{t-1}	-0.0775 (-1.6930)***	-2.5940 (-0.8540)	-18.3776 (-1.2838)
R^{ve}_{t-2}	0.1081 (2.3035)**	-0.1921 (-0.1504)	4.3372 (0.7235)
R^{us}_{t-1}	-0.4378 (-1.9295)***	-1.6698 (-0.8784)	-10.2815 (-0.1321)
ect_{t-1}	-0.1123 (-1.8454)***	0.9720 (0.8741)	-8.9575 (-1.1755)
$F()$		-0.1336 (-0.3410)	-1.1427 (-0.2891)
$F() \times R^{ch}_{t-2}$		9.7636 (1.4120)	25.4553 (0.9364)
$F() \times R^{co}_{t-1}$		-1.5811 (-1.5178)	-23.1165 (-1.1830)
$F() \times R^{mx}_{t-1}$		-3.2426 (-0.6369)	31.9522 (1.2049)
$F() \times R^{mx}_{t-4}$		-0.8880 (-0.5643)	-43.2655 (-1.0428)
$F() \times R^{ve}_{t-1}$		2.5666 (0.8451)	18.3294 (1.2807)
$F() \times R^{ve}_{t-2}$		0.2948 (0.2308)	-4.2410 (-0.7067)
$F() \times R^{us}_{t-1}$		1.3962 (0.7327)	10.0968 (0.1297)
$F() \times ect_{t-1}$		-1.0185 (-0.9157)	8.9107 (1.1693)
γ		231.2550 (0.1681)	179.5180 (1.9612)**
c		-0.0859 (-6.5778)*	0.0542 (72.8312)*
σ	0.0968	0.0751	0.0689
AIC	-4.6073	-5.0441	-5.2187
SBC	-4.7368	-4.6218	-4.7965
R^2	0.2231	0.4395	0.4287
RSS	0.0088	0.6721	0.5644
Diagnostic Test			
Autocorrelation	0.0023	0.3270	0.3270
ARCH	0.0008	0.4440	0.4440
Normality	<0.0001	<0.0001	<0.0001

Table 4 : Chile
Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

Variable	Linear	LSTR	ESTR
Constant	0.0277 (3.1880)*	0.0220 (3.2953)*	-11.1779 (-0.0976)
R^{co}_{t-2}	-0.2175 (-1.8426)***	-0.0744 (-0.8694)	-135.584 (-0.2188)
R^{br}_{t-1}	-0.1271 (-2.8754)*	-0.1475 (-3.8380)*	338.854 (0.0995)
R^{br}_{t-2}	-0.1950 (-3.2751)*	-0.1388 (-3.0457)*	-302.282 (-0.1455)
R^{br}_{t-3}	-0.1589 (-3.0420)*	-0.2144 (-5.5802)*	448.171 (0.1159)
R^{br}_{t-4}	-0.1454 (-3.0290)*	-0.0984 (-2.2550)**	-243.920 (-0.1062)
R^{ch}_{t-4}	0.1727 (2.2918)**	0.1377 (1.7198)***	44.6981 (0.0824)
R^{mx}_{t-2}	0.2450 (2.7468)*	0.1357 (2.0246)**	658.628 (0.1253)
R^{mx}_{t-4}	-0.1695 (-1.8999)***	-0.0556 (-0.8243)	353.911 (0.1028)
R^{ve}_{t-2}	0.0960 (2.1032)**	0.0937 (1.8063)***	74.9000 (0.0962)
R^{us}_{t-1}	-0.6937 (-2.2432)**	-0.4119 (-4.1827)*	237.250 (0.1015)
R^{us}_{t-2}	-0.7089 (-1.5932)	-0.1787 (-1.6718)***	-401.857 (-0.1318)
ect_{t-1}	-0.2134 (-3.6336)*	-0.1786 (-6.5331)*	172.537 (0.0964)
$F()$		0.1451 (4.6859)*	11.2101 (0.0979)
$F() \times R^{co}_{t-2}$		-0.0994 (-0.9270)	135.362 (0.2185)
$F() \times R^{br}_{t-1}$		-0.4572 (-3.8933)*	-338.984 (-0.0995)
$F() \times R^{br}_{t-2}$		-1.2637 (-8.7218)*	302.093 (0.1454)
$F() \times R^{br}_{t-3}$		0.3533 (3.5366)*	-448.342 (-0.1160)
$F() \times R^{br}_{t-4}$		0.0427 (0.4402)	243.771 (0.1062)
$F() \times R^{ch}_{t-4}$		0.1446 (1.2268)	-44.5321 (-0.0821)
$F() \times R^{mx}_{t-2}$		-0.4328 (-2.6563)*	-658.360 (-0.1252)
$F() \times R^{mx}_{t-4}$		-0.8175 (-5.4416)*	-354.081 (-0.1028)
$F() \times R^{ve}_{t-2}$		-0.6254 (-6.2715)*	-74.8108 (-0.0961)
$F() \times R^{us}_{t-1}$		0.7998 (8.1012)*	-237.961 (-0.1018)
$F() \times R^{us}_{t-2}$		-2.8875 (-15.0783)*	401.051 (0.1316)
$F() \times ect_{t-1}$		-0.5280 (-7.2190)*	-172.742 (-0.0965)
γ		1185.2700 (12073.91)*	326.023 (0.8776)
c		0.0574 (1158.81)*	117.892 (171.314)*
σ	0.1007	0.0694	0.1028
AIC	-4.5023	-5.1574	-4.3706
SBC	-4.6893	-4.5663	-3.7795
R^2	0.4146	0.7550	0.4618
RSS	0.0092	0.5349	1.1747
Diagnostic Test			
Autocorrelation	0.6988	0.0097	0.8220
ARCH	0.1249	0.7049	0.9976
Normality	<0.0001	0.8860	<0.0001

Table 5 : Columbia

Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

Variable	Linear	LSTR	ESTR
Constant	0.0121 (1.3210)	0.0176 (1.8137)***	-0.1244 (-0.2423)
R^{mx}_{t-3}	-0.1402 (-1.5718)	-0.1198 (-1.6629)***	-0.8862 (-0.6215)
R^{ar}_{t-3}	0.0606 (1.9397)***	0.0697 (1.2910)	2.7896 (0.7083)
R^{br}_{t-4}	-0.0747 (-1.6429)	-0.0744 (-1.4471)	-3.9026 (-1.1008)
R^{ve}_{t-3}	0.1228 (2.5262)*	0.0992 (1.5414)	0.4442 (0.2147)
ect_{t-1}	-0.0320 (-0.9737)	0.0037 (0.1283)	-0.0369 (-0.0104)
$F()$		-0.0710 (-1.9521)***	0.1439 (0.2801)
$F() \times R^{mx}_{t-3}$		-0.2097 (-0.4656)	0.7489 (0.5179)
$F() \times R^{ar}_{t-3}$		0.1018 (0.7585)	-2.7481 (-0.6978)
$F() \times R^{br}_{t-4}$		0.0014 (0.0101)	3.8657 (1.0899)
$F() \times R^{ve}_{t-3}$		0.6670 (2.4084)*	-0.3251 (-0.1569)
$F() \times ect_{t-1}$		-0.2463 (-2.9806)*	0.0063 (0.0018)
γ		1679.11 (0.0022)	345.096 (2.1153)**
c		0.0565 (1.3411)	81.4323 (96.8193)*
σ	0.1098	0.1055	0.0977
AIC	-4.3758	-4.4022	-4.5562
SBC	-4.4621	-4.1067	-4.2607
R^2	0.0614	0.1853	0.3016
RSS	0.0115	0.0100	0.0086
Diagnostic Test			
Autocorrelation	0.2495	0.3754	0.4727
ARCH	0.0052	0.0015	0.0003
Normality	<0.0001	<0.0001	<0.0001

Table 6 : Mexico
Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

Variable	Linear	LSTR	ESTR
Constant	0.0103 (0.7843)	0.0606 (1.1754)	-0.0447 (-0.5123)
R^{ve}_{t-2}	0.1696 (2.3258)**	0.0267 (0.1820)	0.2938 (2.0613)**
R^{br}_{t-2}	-0.1402 (-2.1409)**	0.0393 (0.2464)	-0.2974 (-1.7474)***
R^{co}_{t-1}	0.2424 (2.6300)*	0.6490 (2.0733)**	0.0801 (0.6043)
R^{mx}_{t-2}	0.2604 (2.4573)*	0.2792 (0.8872)	0.1289 (0.5428)
R^{us}_{t-1}	-0.7569 (-1.9182)***	0.1152 (0.1058)	0.5191 (0.2831)
ect_{t-1}	0.0568 (1.1725)	0.3395 (2.2120)**	-0.2222 (-1.9050)***
$F()$		-0.1751 (-1.4420)	0.0775 (0.7658)
$F() \times R^{ve}_{t-2}$		0.2609 (1.0854)	-0.2673 (-1.2680)
$F() \times R^{br}_{t-2}$		-0.4169 (-1.4755)	0.2996 (1.2849)
$F() \times R^{co}_{t-1}$		-0.5439 (-1.4714)	0.5740 (1.5639)
$F() \times R^{mx}_{t-2}$		-0.0444 (-0.0884)	0.2632 (0.5050)
$F() \times R^{us}_{t-1}$		1.7519 (1.1406)	-1.1083 (-0.6480)
$F() \times ect_{t-1}$		-0.5455 (-2.9476)*	0.5881 (4.1045)*
γ		2.6338 (1.3247)	0.5594 (0.9262)
c		0.0149 (1.0010)	0.0537 (6.6783)*
σ	0.1469	0.1392	0.1361
AIC	-3.7876	-3.8362	-3.8806
SBC	-3.8883	-3.4984	-3.5428
R^2	0.1273	0.2696	0.3013
RSS	0.0205	0.0171	0.0164
Diagnostic Test			
Autocorrelation	0.3376	0.9052	0.9851
ARCH	0.0143	0.2677	0.3957
Normality	<0.0001	<0.0001	<0.0001

Table 7 : Venezuela
Notes: Values in parentheses are t-statistics. Significance at 1%, 5% and 10% is shown by *, **, and *** respectively. Diagnostic test results are p-values. Tests for autocorrelation and ARCH are LM tests up to lag 6. Normality is the Lomnicki-Jarque-Bera test.

	LSTR			ESTR		
	γ	c	RSS	γ	c	RSS
			Argentina			
R^{ar}_{t-1}	34	0.1945	3.2470	1	0.0048	3.558
R^{us}_{t-1}	117	0.0385	3.7883	150	0.0454	3.102
R^{la}_{t-1}	200	0.0304	3.9498	58	0.0251	3.676
$Time$	200	18.70	**3.1990**	150	13.00	**2.733**
			Brazil			
R^{br}_{t-1}	200	-0.1811	**3.764**	75	-0.1811	3.759
R^{us}_{t-1}	23	-0.0333	4.454	146	0.0570	**3.552**
R^{la}_{t-1}	109	-0.0593	4.395	150	-0.0593	3.638
$Time$	200	13.00	4.627	150	24.40	4.251
			Chile			
R^{ch}_{t-1}	74	-0.0748	**0.6892**	1	0.0876	0.8992
R^{us}_{t-1}	131	0.0570	0.8467	150	0.0547	**0.5680**
R^{la}_{t-1}	200	-0.0646	0.7790	144	-0.0646	0.6681
$Time$	200	124.10	0.9385	107	124.10	0.6042
			Columbia			
R^{co}_{t-1}	190	0.0671	0.6770	150	0.1001	0.6456
R^{us}_{t-1}	200	0.0540	**0.5264**	55	0.0562	0.6136
R^{la}_{t-1}	113	-0.0565	0.6855	67	-0.0609	0.5898
$Time$	102	122.30	0.5386	150	122.30	**0.5779**
			Mexico			
R^{mx}_{t-1}	3	-0.1021	1.4555	150	0.0517	1.395
R^{us}_{t-1}	143	0.0570	**1.4158**	150	0.0570	1.234
R^{la}_{t-1}	29	-0.0910	1.4279	150	0.0040	1.363
$Time$	200	67.15	1.5069	150	81.40	**1.218**
			Venezuela			
R^{ve}_{t-1}	9	0.1643	2.4688	93	0.1165	2.577
R^{us}_{t-1}	3	0.0163	**2.3830**	1	0.0539	**2.287**
R^{la}_{t-1}	187	-0.0520	2.5141	123	-0.0654	2.459
$Time$	200	122.25	2.4811	150	92.00	2.365

Table A1 : Grid search results
Notes: Figures in bold are minimum RSS values.

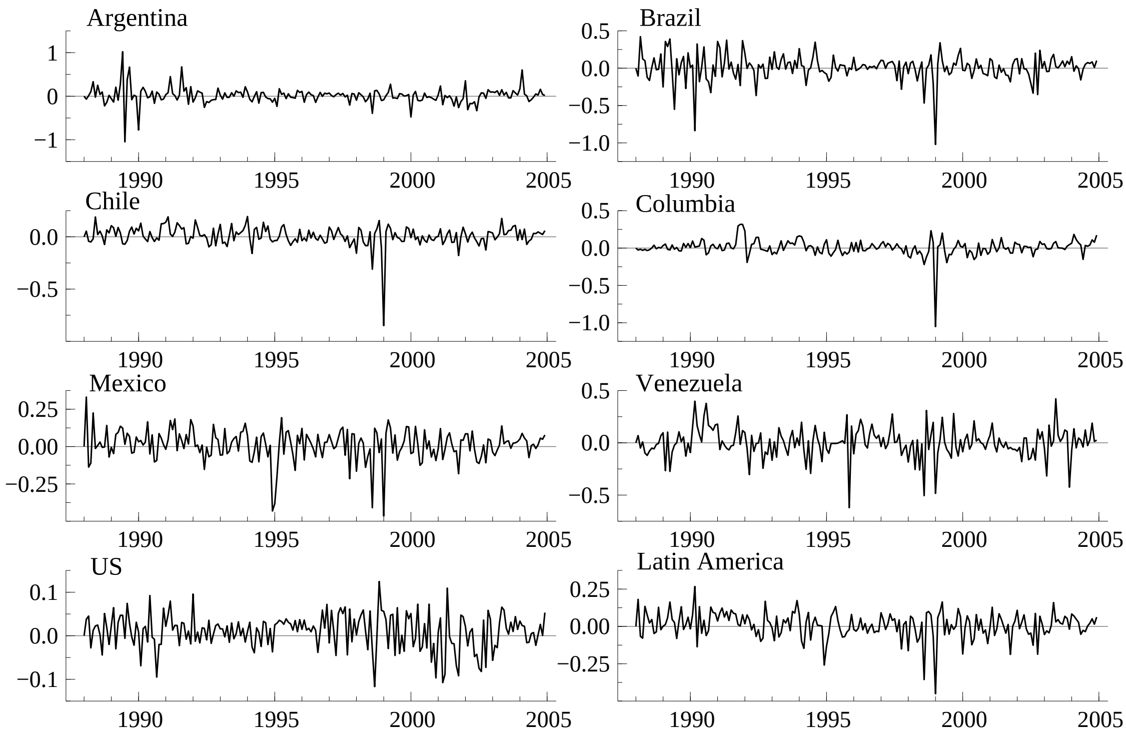

Figure 1: Stock Returns February 1988 - December 2004.

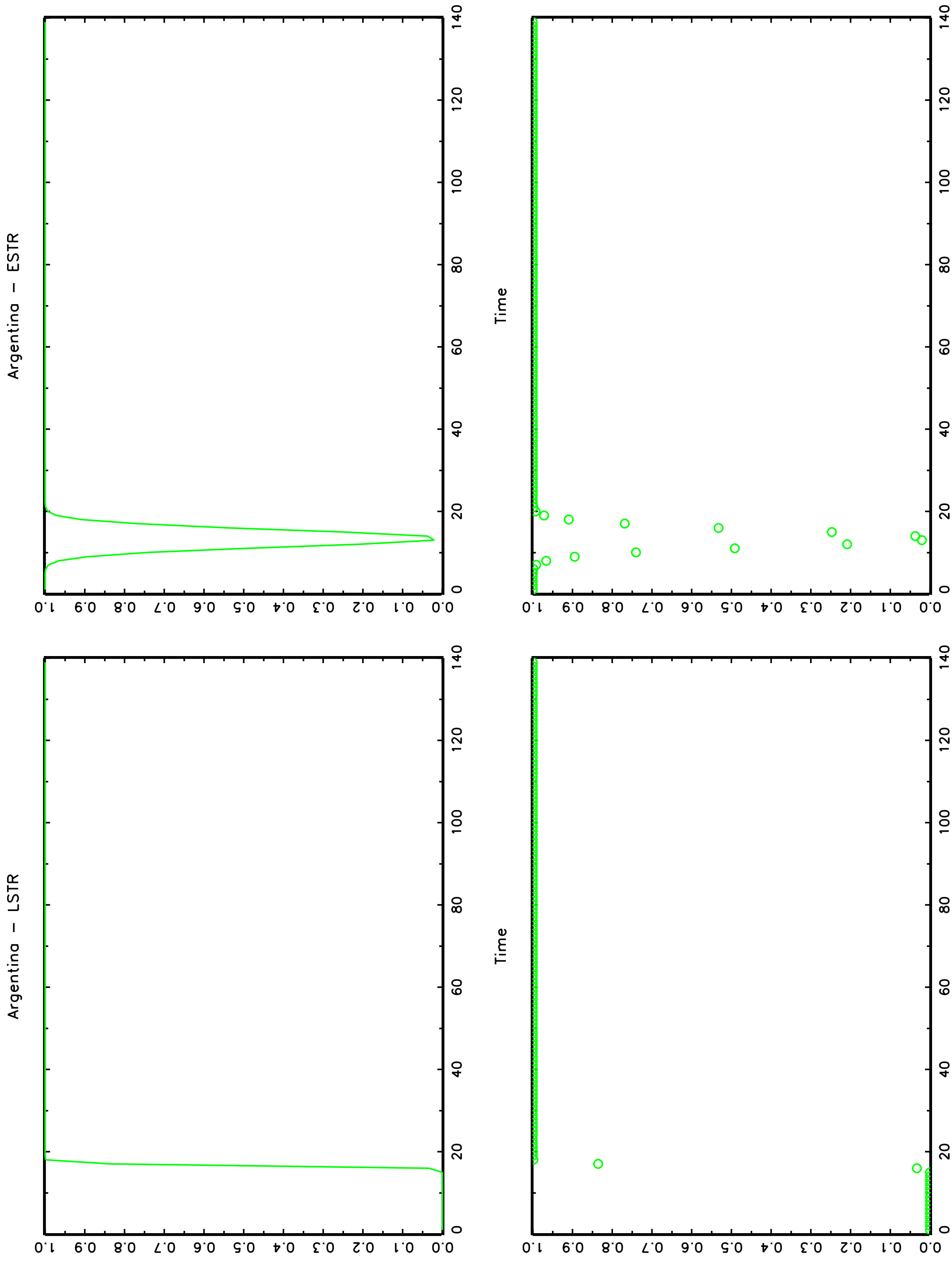

Figure 2: Argentina - Transition Functions

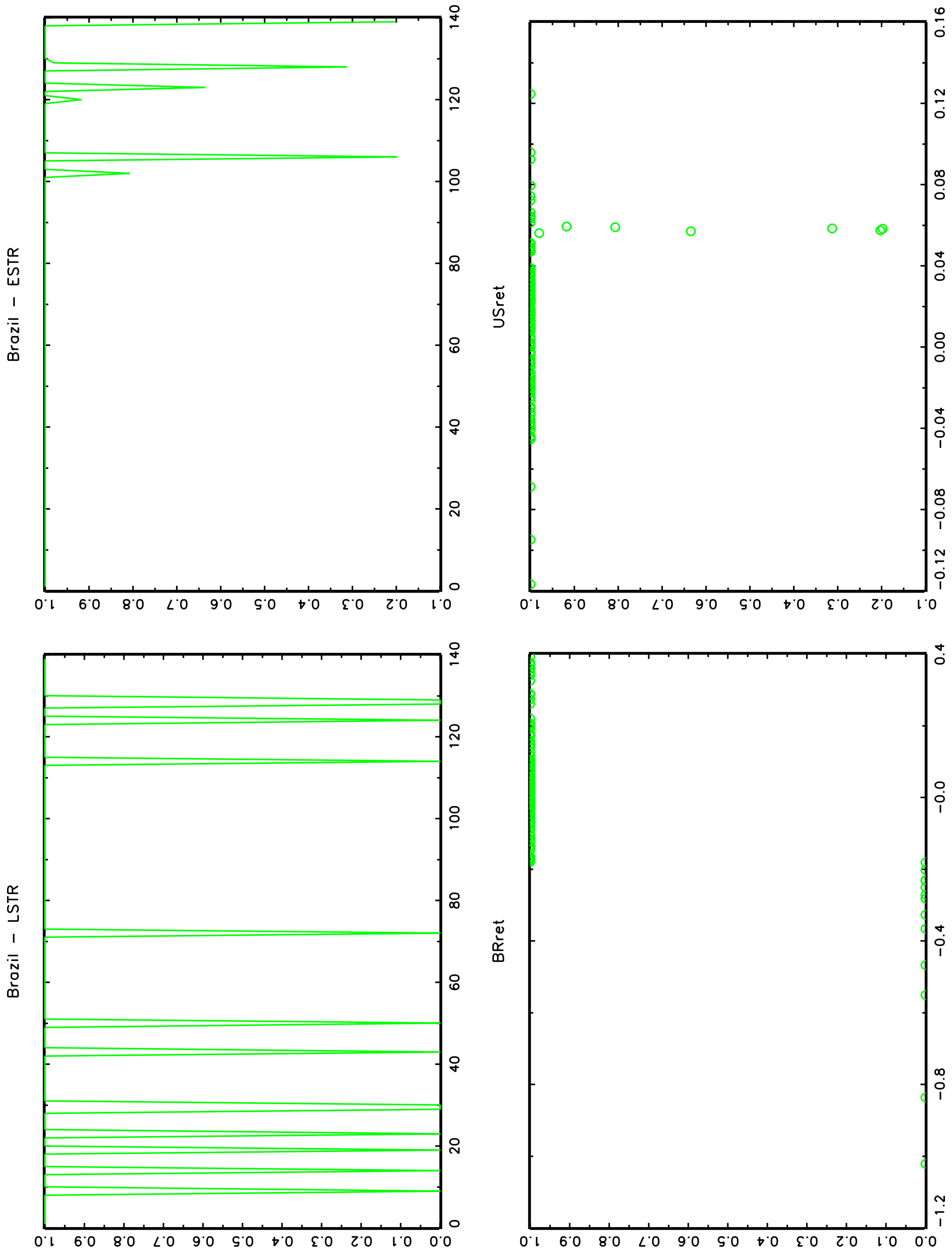

Figure 3: Brazil - Transition Functions

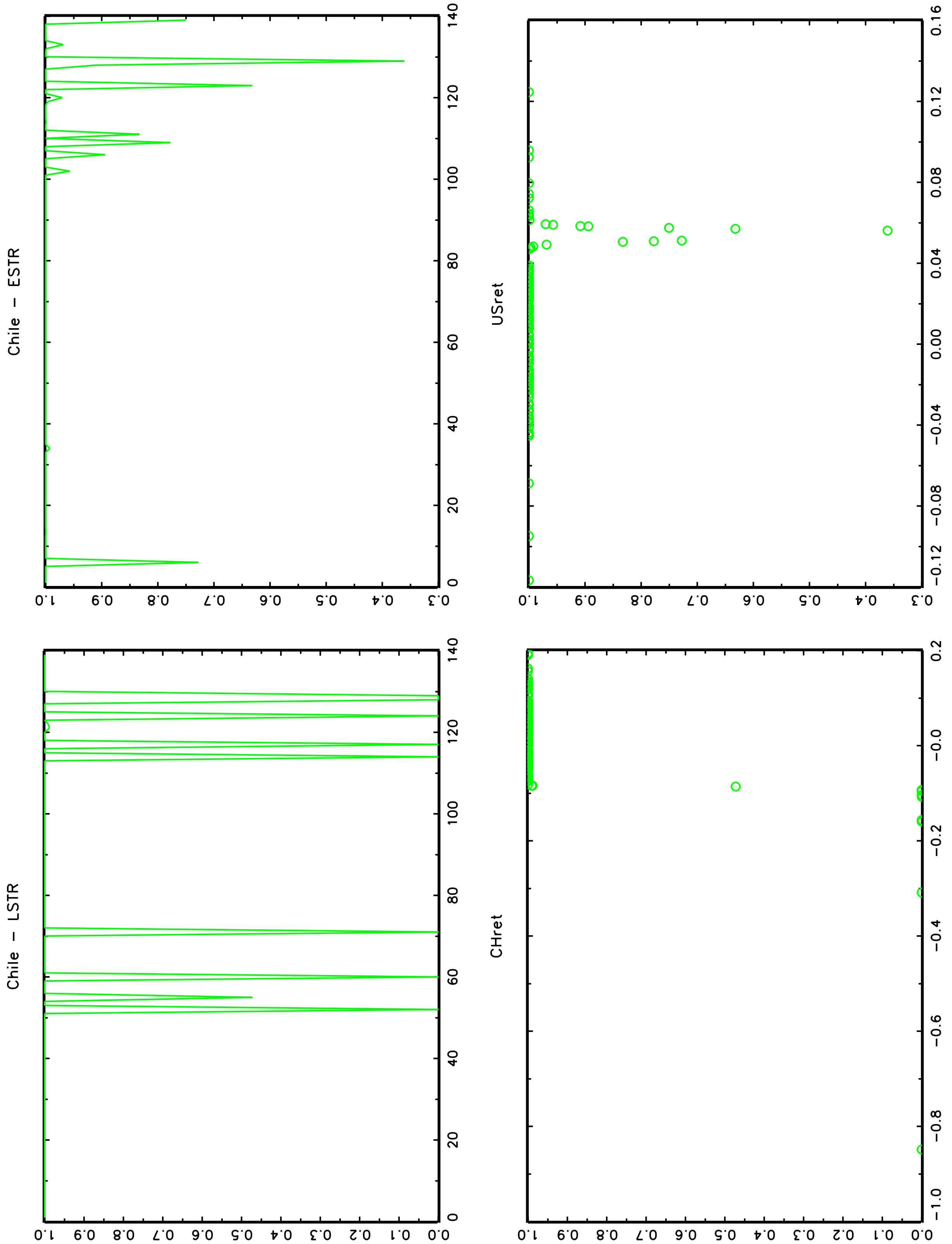

Figure 4: Chile - Transition Functions

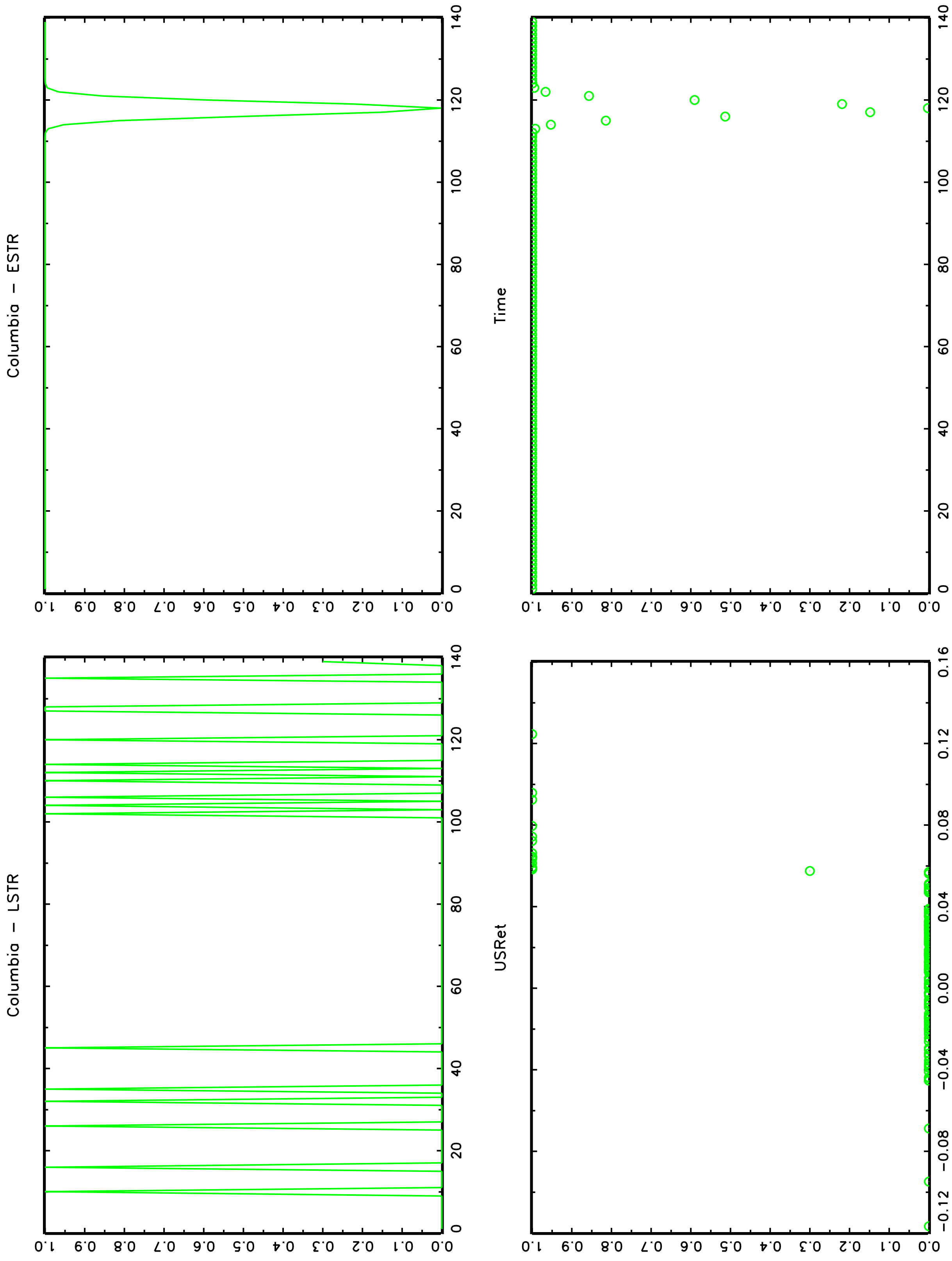

Figure 5: Columbia - Transition Functions

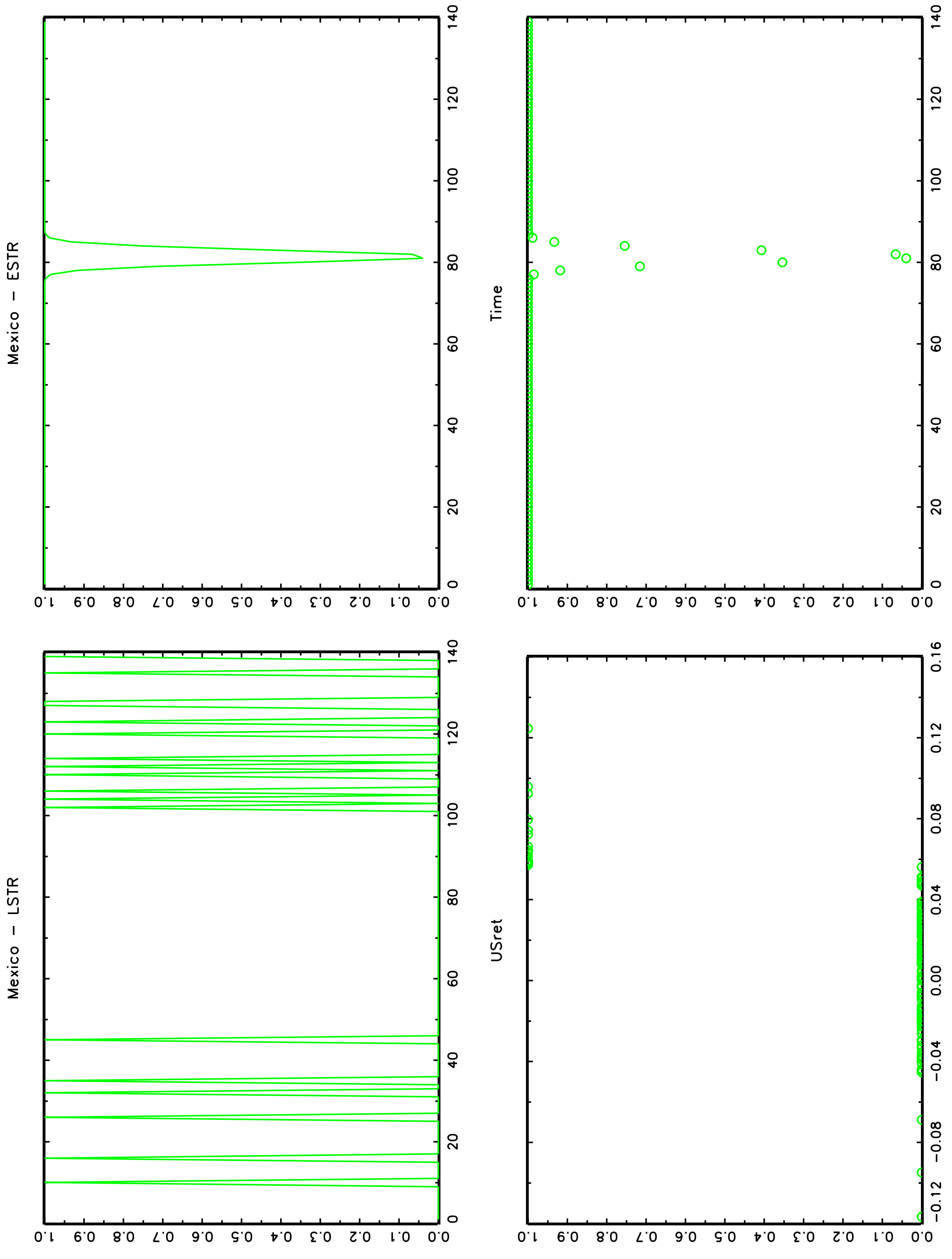

Figure 6: Mexico - Transition Functions

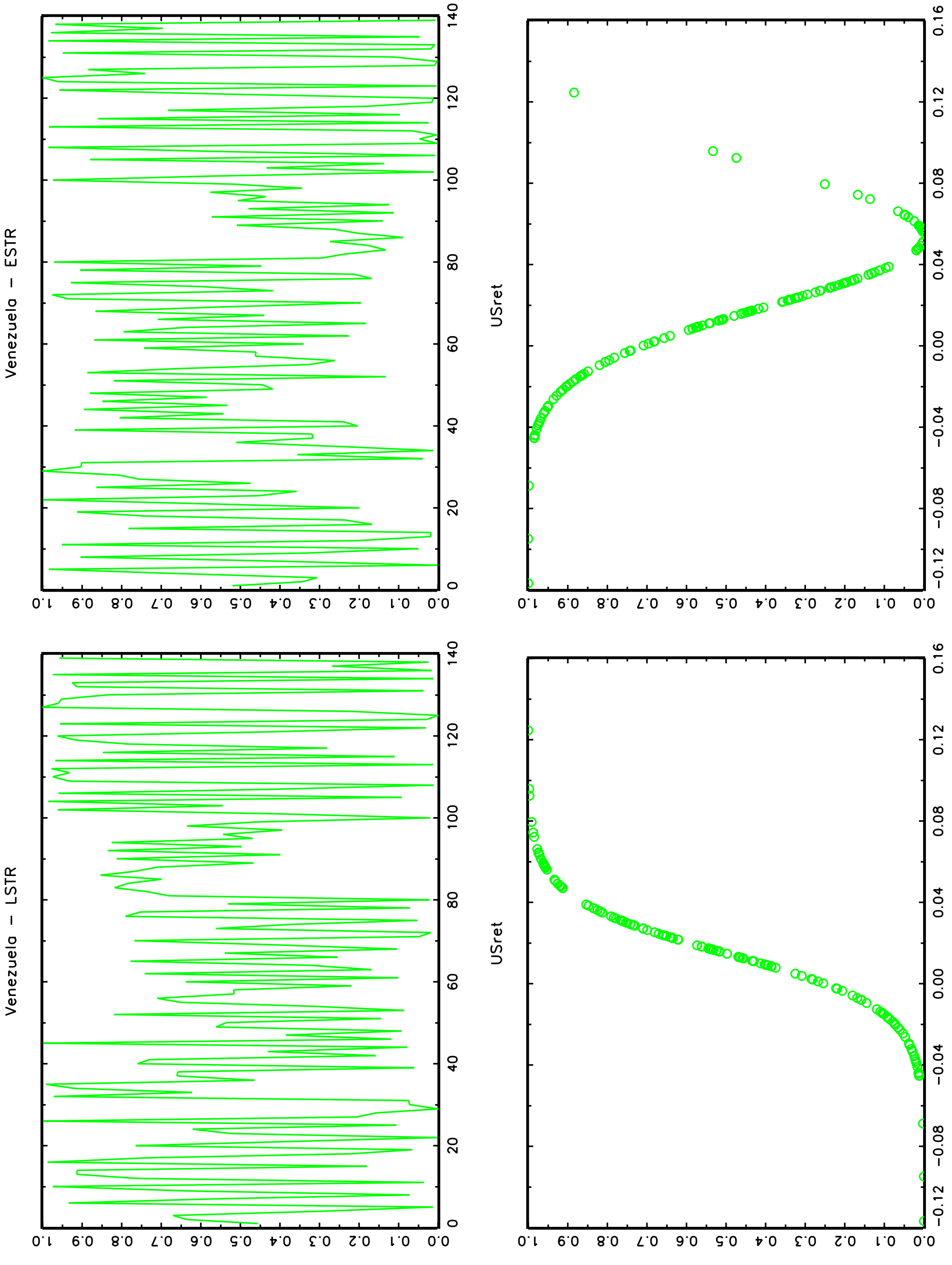

Figure 7: Venezuela - Transition Functions