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INTEREST RATE VOLATILITY AND CONTAGION IN EMERGING MARKETS: EVIDENCE FROM THE 1990s

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ABSTRACT

In this paper we use high frequency interest rate data for a group of Latin American countries to analyze the behavior of volatility through time. We are particularly interested in understanding whether periods of high volatility spillover across countries. Our analysis relies both on univariate and bivariate switching volatility models. Our results indicate that high-volatility episodes are, in general, short-lived, lasting from two to seven weeks. We find some weak evidence of volatility co-movements across countries. Overall, our results are not overly supportive of "contagion" stories.

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I. Introduction

After the Mexican crisis of 1994, most emerging economies experienced an increase in interest rate volatility (See Figure 1). This phenomenon has affected policy debates in, at least, three ways. First, a number of authors have argued that increased interest rate volatility is largely the result of "excessive" capital mobility, see Stiglitz (1999). According to this view the imposition of controls on capital inflows, similar to those used by Chile during 1991-98, would help countries reduce externally induced financial instability, see Krugman (1999). Second, some authors have argued that increased interest rate volatility is inherent to floating exchange rate regimes. This argument has, in fact, become central in recent discussions on the merits of "dollarization" in emerging economies, see Hausmann (1999). Third, the extent of financial volatility – and, in particular, of changes in volatility – has played an important role in discussions on whether emerging markets have indeed been subject to "contagion." Forbes and Rigobon (1999), for instance, have argued that the simple analysis of the behavior of correlation coefficients through may provide a misleading picture of "contagion," if the country in question experiences changes in volatility's regimes.

In this paper we use high frequency interest rate data for five emerging countries – Argentina, Brazil, Chile, Hong Kong and Mexico – to analyze the recent evolution of interest rate volatility. We are particularly interested in five interrelated issues:

- Is it possible to statistically detect changes in interest rate volatility processes in these five countries?
- If so, how many "volatility states" can be identified?
- How common are "high volatility" states? And, for how long have they lasted?
- Do dates of "high volatility" states (approximately) coincide across countries?
- Can we statistically identify groups of countries that jointly experience "high volatility" states?

The countries in our sample provide a very diverse experience in terms of macroeconomics institutions, policies and experiences. During the period under consideration Chile and Brazil had controls on capital inflows, while the other three countries didn't. In terms of exchange rate regimes, Argentina and Hong Kong had a currency board, Mexico has had since 1995 a floating system, Chile floated within broad bands, and until January 1999 Brazil had a slowly crawling exchange rate regime. Analyzing the cross-country transmission of interest rate volatility, would help shed light on a number of important macroeconomics problems that are germane to the design of the new international 'financial architecture." Although we don't expect to solve current debates on "contagion," we believe that the analysis of five issues defined above will provide important information on the issue.

We address the five questions defined above by using both univariate, as well as multivariate techniques. We first follow a variant of Hamilton and Susmel's (1994) SWARCH methodology, to identify breakpoints in an ARCH model of the conditional variance. A particular attractive feature of this approach is that it allows us to date periods of high volatility. We find that, in most (but not all) countries the "high volatility states" are rather short-lived. We also find that periods of "high volatility" tend to roughly coincide across some countries. We further explore the degree of co-movement in volatility by developing a multivariate extension of the SWARCH model. Since this model is highly intensive in computing time, we restrict its application to pairs of countries.

Our analysis is in a spirit similar to that studies on the effects of 1987 stock market crash on financial volatility across countries (Bennett and Kelleher 1988, King and Wadhwani 1990). Other papers that deal with cross country volatility include the studies on "meteor showers" by Engle and Ng (1993), Ito, Engle and Lin (1990, 1992), and Hamano, Ng and Masulis (1990), and the studies on equity markets time-varying correlations by Longin and Solnik (1995), and the Ramchand and Susmel (1998). In contrast to our paper, most work on switching interest rate volatility have tended to focus on only one country. Hamilton (1989), for example, shows that the time series behavior of U.S. interest rates changed significantly during the 1979-1982 Federal Reserve's monetarist experiment. Ball and Taurus (1995), Gray (1996), and, more recently, Kalimipalli and Susmel (1999) have used switching models to analyze the volatility of U.S. interest rates.

The paper is organized as follows: Section I is the introduction. In Section II we discuss the data used in the analysis. In Section III, we use univariate SWARCH models to analyze interest rate volatility in our five countries. Section IV contains the results for the multivariate case. Finally, section V is the conclusions.

II. Interest Rates in Selected Emerging Economies During the 1990s: A Preliminary Analysis

Our analysis deals with weekly interest rate behavior in Argentina, Brazil, Chile, Hong Kong and Mexico during the 1990s. The data were taken from the *Datastream* data set, and cover the longer period for which there is information. For the case of Argentina, we consider peso denominated 30 day deposit rates (ARS), as well as dollar denominated 30 day deposit rates (USD). The ARS interest rate data covers the period from April 5, 1991 to April 16, 1999, for a total of 420 observations. The USD interest rate data covers the period from May 7, 1993 to April 16, 1999, for a total of 311 observations. For Chile, we use the Chilean 30-day CD interest rate in pesos (CLP). The CLP sample starts on January 7, 1994, for a total of 276 observations. The Brazilian data (BRR) correspond to the CDI (middle) rate, and cover the April 18, 1994 through April 16, 1999 period. The Mexican interest rate is the 28-day deposit rate in pesos (MXP). The MXP interest rate sample starts on January 3, 1992, for a total of 381 observations. For Hong Kong, we use the interbank 30-day rate in Hong Kong dollars (HKD). The HKD interest rate data covers the whole sample; that is, we have a total of 433 observations.

In Figure 1 we present the data in first differences; in Figure 2 we present it in levels. The first differences data clearly show that, in all five countries, interest rates have experienced changes in volatility during the period under study. Each individual case, however, presents its own peculiarities. In some countries (Hong Kong) volatility increases around 1997, in others (Argentina) volatility shifts several times from high to low, and back to high. In yet others (Mexico) volatility appears to be high throughout most of the period.

Figure 2, on interest rate levels, is quite interesting and captures the financial upheaval of the 1994-1999 period. Consider first the case of Argentina: Throughout most of the period the differential between peso and US Dollar rates declined, indicating that the currency risk was becoming smaller and smaller. Also, both Argentine series exhibit spikes in the periods surrounding the Mexican (early 1995), East Asian (October-November 1997), Russian (August 1998), and Brazilian (January 1999) crises. Notice, however, that the magnitude of these spikes is very different. Argentine interest rates were subject to the largest spike in the aftermath of the Mexican crises; the second largest was associated with the Russian crises. Although Chile's rates also appear to have been affected by the crises, the magnitude of the spikes appear to be smaller than those in the Argentine data. The data on Brazil show that, as the real plan became ingrained, interest rates experienced a declining trend. However, as in our other countries they did experience several jumps during the period under study. These appear to have happened at times that roughly coincide with the major currency crises of the period.

Not surprisingly, Mexican interest rates increased sharply in the aftermath of the Mexican peso crisis of December of 1994. However, as the figure shows, Mexican interest rates were also sensitive to major international crises. In fact, Mexico's interest rates were particularly affected by the collapse of the Russian Ruble in August, 1998. Finally, the data on Hong Kong show a small spike in the period following the Mexican crisis of December 1994, a major jump at the time of the East Asian crisis and, again, a spike around the time of the Russian crisis

In Table 1 we present summary statistics for the first differences of our six interest rates. More specifically, this Table contains information on the mean, standard deviation, skewness coefficient, Kurtosis coefficient, the Jarque-Bera Normality test (JB), and Ljung-Box test (LB). The JB statistic follows a Chi-squared distribution with two degrees of freedom. The LB(q) is an autocorrelation test, where q represents the number of lags included in the computation of the LB statistic. The LB test follows a chi-squared distribution with q degrees of freedom. All these series show the typical non-normality of financial time series (see the JB test results). The high kurtosis coefficient is also typical of high frequency financial time series, and it is behind the rejection of normality. The Ljung-Box (LB) statistics suggest significant autocorrelation in the levels and in the squared levels, which, in turn, suggests evidence for a time-varying variance.

III. Interest Rate Volatility and Breakpoints: Univariate Analysis

III.1 The Model

Most studies on interest rate volatility are based on the estimation of GARCH-type models (Campbell, Lo and MacKinlay 1997). Although standard GARCH models are parsimonious, and are able to capture the time varying nature of volatility, they fail to capture structural shifts in the data that are caused by low probability events, such as the Crash of 1987, the so-called Tequila effect, and recessions, among other. In this paper we use the model of Hamilton and Susmel (1994) to explicitly model the dynamics of switching variance. Hamilton and Susmel (1994) modify the ARCH specification to account for such structural changes in data and propose a Switching ARCH (SWARCH) model. The SWARCH (K,q) model used in this paper is:

(1) $\Delta r_t = a_0 + a_1 \, \Delta r_{t-1} + \varepsilon_t, \qquad \varepsilon_t|I_{t-1} \sim N(0,h_t)$

(2) $h_t/\gamma_{st} = \alpha_0 + \Sigma_{i=1} \, \alpha_i \, \varepsilon^2_{t-i}/\gamma_{st-i} \qquad i = 1,2,...,q, \text{ and } s_t=1,2,..,K,$

where the γ's are scale parameters that capture the change in regime. One of the γ's is unidentified and, hence, γ_1 is set equal to 1.

The SWARCH model also requires a formulation of the probability law that causes the economy to switch among regimes. One simple specification is that the state of the economy is the outcome of a K-state Markov chain that is independent of r_t for all t:

(3) $\text{Prob}\,(s_t = j|s_{t-1} = i, s_{t-2} = k,..., r_t, r_{t-1}, r_{t-2},...) = \text{Prob}\,(s_t = j|s_{t-1} = i) = p_{ij}.$

Under this specification, the transition probabilities, the p_{ij}'s, are constant. For example, if the economy was in a high volatility state last period (s_t=2), the probability of changing to the low volatility state (s_t=1) is a fixed constant p_{21}.

As a byproduct of the maximum likelihood estimation, Hamilton (1989) shows that we can make inferences about the particular state of the security at any date. The "filter probabilities," $p(s_t,s_{t-1}|r_t,r_{t-1},..,r_{-3})$, denote the conditional probability that the state at date t is s_t, and that at date t-1 was s_{t-1}. These probabilities are conditional on the values of r observed through date t. The "smooth probabilities," $p(s_t|r_T,r_{T-1},...,r_{-3})$, on the other hand, are inferences about the state at date t based on data available through some future date T (end of sample). For a two-state specification, for example, the smooth probabilities at time t are represented by a 2x1 vector denoting the probability estimates of the two states. That is, the smooth probabilities represent the ex-post inference made by an econometrician about the state of the security at time t, based on the entire time series.

II. 2 Results

As a first step in our analysis of interest rate volatility we estimated, for each one of the series, a simple AR(1)-GARCH(1,1) model. To avoid the problems associated with non stationary time series, we work with first differences.[1] The results, which are reported in Table 2 finds significant ARCH effect for all the series. Moreover, with the exception of the CLP's interest rate, the LB statistics for the standardized residuals can not find any further evidence of autocorrelation in the level of the standardized residuals or in the squared standardized residuals. The size of α_1 is unusual for high frequency financial time series. For example, for the ARS, USD and BRR, α_1 is unusually high. Also, for the BRR rate, and the ARS-USD (not shown), β_1 is unusually low. Moreover, for four of the six series, the sum of α_1 and β_1 is a bit higher than one, which makes shocks to the conditional variance increasingly persistent over time.[2] Lamoureux and Lastrapes (1990), Cai (1994) and Hamilton and Susmel (1994) argue that the observed high persistence of shocks to the conditional variance is a sign of structural change in variance.

We can formally test the null hypothesis of no regime-switch by using the likelihood ratio test proposed by Hansen (1992, 1994). A likelihood ratio test of this null hypothesis does not have the usual limiting chi-squared distribution, because the parameters p_{ij} are unidentified under the null. Hansen (1992) proposes a test, based on empirical theory process, that is able to provide an upper bound to the asymptotic distribution of standardized likelihood ratio statistics, even when conventional regularity conditions (such as unidentified parameters) are violated.[3] We calculate

[1] We also worked with levels for interest rates. We used a specification where the AR(1) coefficient is state dependent, allowing in at least one of the states for interest rates to be non-stationary. The results are similar to the results presented in this section. Moreover, we find that the volatility states are determined by the variance, and not by the different AR(1) coefficients.
[2] Again, it is usual to observe, in high frequency financial series, the so-called Integrated GARCH model, where $\alpha_1+\beta_1=1$.
[3] To get around the problem of no identified parameters under the null, Hansen (1994) defines a function

Hansen's test for all the series under the null hypothesis of no regime-switching, using a four-lag Newey-West correction. The standardized likelihood ratio tests and their corresponding p-values are reported in Table 2. For all the series, the null hypothesis of no regime-switch can be rejected at the 5% level. The Hansen test for Chile's CLP rate provides a standardized likelihood ratio test of 2.03, which is slightly lower than the simulated 1% upper bound critical value of 2.05.

After rejecting the hypothesis of no-regime switch, the next step is to use the Switching ARCH (SWARCH) model of Hamilton and Susmel (1994), to identify periods of unusually high volatility. We fit different SWARCH specifications. We estimated models with K=2 to 4 states and q=0 to 3 autoregressive terms. We estimated SWARCH models with asymmetric effects, as proposed by Glosten, Jaganathan and Runkle (1993) and with t-distributed conditional errors. Our results suggest that either two- or three-state SWARCH models may be appropriate for the majority of the series[4]. In the rest of this section, and due to space considerations, we focus on the case of three volatility states. The reader should keep in mind, however, that the results discussed here largely apply to the case of two states (high and low) only.

The results obtained are reported in Table 3. Several interesting findings emerge from this table. First, the best descriptive model for all series is a model with three states. That is, for each of our six interest rates it is possible to distinguish a "low," a "moderate" and a "high" volatility state. Second, for all the series we notice that using the SWARCH(K,q) model causes the ARCH effects to be reduced. Three, the switching parameters, the γ_i's, are significantly different than one in all

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$$q_t(\zeta) = L_t[\zeta,\lambda(\zeta)] - L_t[\zeta_0,\lambda(\zeta_0)],$$

where $L_t[\zeta,\lambda(\zeta)]$, represents the conditional log likelihood of the tth observation when evaluated at ζ and $\lambda(\zeta)$. The parameters ζ and λ represent a partition of the parameter space. For the two-state case $\zeta=(p_{11},p_{22},\gamma_2)$. Under the null hypothesis of no regime-switching $\zeta=\zeta_0=(1,0,1)$. We investigated a grid containing 345 possible parameters for ζ under the alternative hypothesis, with Z consisting of these 345 possibilities considered. For any ζ, $\lambda(\zeta)$ is estimated by maximizing the likelihood with respect to λ, given ζ. Hansen (1994) proposes the following standardized test:

$$LR = \max_{\zeta\varepsilon Z}\ T\, mq(\zeta)/[\Sigma_t\,(q_t(\zeta) - mq(\zeta))^2]^{1/2},$$

where mq is the mean of q_t. Hansen shows that, if the null hypothesis of no regime-change is true, then for large samples the probability that LR would exceed a critical value z is less than the probability that a Monte Carlo simulated statistic would exceed the same value z.

[4] Standard likelihood ratios reject, with the exception of Chile, the null hypotesis of a two-state model against the three-state model. Standard likelihood ratio tests, however, cannot be used, because the parameters p_{ij}, for the third state, are unidentified under the null hypothesis of two-states. Precise Hansen (1992) tests are computationally expensive in this case, because of the large number of parameters needed for the grid. For Argentina, preliminary (i.e., not very fine grid) tests are unable to reject the null hypothesis of two states against the alternative hypothesis of three

three series. Fourth, we find no evidence for an asymmetric effect of negative news on conditional volatility.

The results for the estimated γ_i's are particularly interesting. As Hamilton and Susmel (1994) have shown, γ_j provides an estimate of the ratio of the conditional variance in state j, relative to the "low volatility" state. That is, in our three-states case, γ_2 provides information on how much higher is moderate volatility relative to low volatility. Likewise, γ_3 captures the estimated ratio of high relative to low volatility. For example, for Argentina's ARS peso-denominated interest rate, the moderate volatility state is on average around four times higher than that in the low volatility state; and the high volatility state is on average thirty five times higher than that in the low volatility state. Interestingly enough, the highest ratio of average high to low state is in Brazil (128 times); Hong Kong follows closely, with an estimated γ_3 of 79. Chile, on the other hand, has the lowest estimated $\gamma_{3,}$ with a still remarkable value of 20.

We are interested in checking if the regimes are also influenced by the mean. We fit two different standard Hamilton (1989) models, with three states: one allowing for mean switching only and the other one allowing for simultaneous mean and variance switching. In Table 3, we report the likelihood function of each model. For the first model, we tend to find that the first and third states play the role of dummy variables, identifying outliers-, the fit of the model is inferior to the SWARCH model. When we allow for simultaneous mean and variance switching we find that the states are primarily driven by variance switching, not mean switching. Moreover, the states, determined by the smoothed probabilities, are similar to the states that were determined by the SWARCH model.

The first panel of Figure 3 plots weekly interest rate changes in Argetina's peso denominated interest rates (ARS); the other three panels plot the smoothed probabilities, $\text{Prob}(s_t{=}i|y_T,y_{T-1},...,y_{-3})$ for the change in nominal interest rates. The second panel plots the smoothed probability that the economy was at state 1 (low volatility) at time t, the third panel plots the smoothed probability that the economy was at state 2 (moderate volatility) at time t, and the fourth panel plots the smoothed probability that the economy was at state 3 (high volatility) at time t. The observations are classified following Hamilton's (1989) proposed method for dating regime switches. According to this procedure, an observation belongs to state i if the smoothed probability $\text{Prob}(s_t{=}i|r_T,r_{T-1},...,r_{-3})$ is higher than .5. Changes in ARS interest rates switch between the moderate

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states.

volatility state and the high volatility state during the first four and a half years. In the second half of 1995, ARS interest rates change to the low volatility for more than two years. Then, during the last quarter of 1998, there is a short shift towards the high volatility event, followed by another three months in the moderate volatility state. Then, during the third quarter of 1998, there is a new shift towards high and then moderate volatility.

A particularly interesting feature of the results in Figure 3 is that, at a first glance, it appears that that since late 1994 the stays of the ARS interest rates in the high volatility state correspond (roughly) to foreign (exogenous) events. For example, all the post-1994 moves to the high volatility state coincide with the Mexican crisis, the Asian crisis, the Russian crisis, and the Brazilian crisis, respectively. These results may suggest that indeed Argentina was subject to some form of "volatility contagion" during these crises upheavals. We analyze this hypothesis in greater detail in the next section, where we use a bivariate switching volatility model to investigate whether we can reject the hypothesis of volatility co-movements and independence in pairs of countries. It is important to notice, however, that the "high volatility" state detected in 1991, 1992 and mid-1993 cannot be attributed – or at least nor easily – to external events. Indeed, we interpret this period of high instability as reflecting the low degree of credibility enjoyed by Argentina's currency board during its early years.[5]

The results for Argentina's dollar-denominated interest rates, not reported here due to space considerations, are somewhat similar. We can detect ten changes of regimes between the low and moderate volatility states. Similar to the peso-denominated ARS results, all the changes to the high volatility state are related to exogenous events: the Mexican crisis, the Asian crisis, the Russian crisis and the Brazilian crisis.[6]

Figures 4 through 7 correspond to the results obtained for our other 4 countries. The results are quite interesting and show that for Brazil and Chile the periods of "high volatility" are relatively short lived. Moreover, Chile does not appear to have suffered an increase in volatility – defined as a move to the "high" state – during late 1994 or early 1995. This suggests, quite strongly we believe, that Chile was immune to "contagion" coming from the Mexican "Tequila" crisis. Mexico and Hong Kong, however, do show prolonged periods of high volatility. In the

[5] See Ruge-Murcia (1995) for a "credibility" interpretation of switching states along the lines discussed here.

[6] We also investigated whether these series exhibited simultaneous mean and variance switching. For every series we found that the states are primarily driven by variance switching, not mean switching.

case of Mexico, our results in Figure 7 suggest a "high volatility state" that extends from late 1994 through most of the first half of 1995. This, of course, corresponds to the Mexican peso crisis and, for Mexico, responds to domestic upheaval. As Figure 6 shows, Hong Kong shifts to a "high volatility" state in late October, 1997, and stays in that states for almost a year. The beginning of this state corresponds, of course, to the attack on the Hong Kong currency board and to the heightening of the East Asian crisis. The very long period during which Hong Kong is in the "high volatility" state is surprising, and does not correspond to what we observe to the other crisis countries in the sample (Mexico and Brazil).

Figures 3 through 5 distinctively show that Argentina, Brazil, Chile and Mexico shifted to a high interest rate volatility state sometime between late August-mid September 1998. This of course coincides with the Russian crisis and suggests that there was a fairly rapid transmission of financial instability across emerging economies. Interestingly enough, our analysis does not allow us to know whether Hong Kong interest rate instability was affected by the Russian crisis. As Figure 6 shows, Hong Kong continued to exhibit a "high volatility" state at the time of the Russian default. What we cannot tell, however, is if this corresponds to a continuation of its own crisis, if it reflected the Russian episode, or if it was a combination of both. Finally, it is interesting to note from these figures that, while Argentina and Chile experienced a shift to high volatility in the period immediately following the Brazilian crisis of 1999, Hong Kong and Mexico did not suffer increased interest rate instability at the time.

Table 4 contains a summary of our findings on the extent and duration of high volatility in the periods surrounding the Mexican, East Asian, Russian and Brazilian currency crises of the 1990s. Each entry, in Table 4, provides, for each of our countries, a starting date for the high volatility state, as well as the number of weeks the economy was in the high volatility state. Although we are reluctant to label these episodes as "volatility contagion," we argue that it is suggestive that our countries experienced a significant increase in volatility in the period ***following*** a major crisis. It is also interesting (and reassuring) to note that the crises countries themselves are indeed the first to experience a shift to the high volatility state. The fact that the dates of high volatility states ***roughly coincide***, is indeed suggestive, but does not constitute statistical evidence in favor of either the "volatility co-movement" or the "volatility contagion" hypotheses. In order to investigate this issue formally, it is necessary to extend the SWARCH model used in this section to the multivariate case. This we do in the section that follows.

IV. Cross Country Volatility Co-Movements: Multivariate Results

The results from the preceding section provide some preliminary evidence of (roughly) coincidental volatility switches across countries. In this section, we explore this issue further by developing a bivariate switching volatility model.[7] We take advantage of the dating abilities of the Hamilton (1989) filter to test whether volatility states are *independent* across countries. Generally speaking, volatility states are *independent*, if financial markets across countries are segmented. If, however, financial markets are highly integrated and shocks are transmitted rapidly across countries, we would expect that the hypothesis of independence would be rejected.

To test the above hypotheses, we estimate a multivariate formulation of the SWARCH model. As it turns out, this multivariate SWARCH model is extremely intensive in computation time. This means that the econometrician has to make some choices in terms of the number of volatility states, and number of countries included in the analysis. In order to keep the number of parameters tractable, in this section we consider the case of two countries and two volatility states (high and low). That is, we estimate a bivariate SWARCH model. In order to organize the discussion, and reduce the dimensionality of the problem, we concentrate on Mexico-"Other country" and Hong-Kong-"Other country" pairs. This already gives us six two-country combinations. We focus on Mexico and Hong Kong -- which we call (potential) volatility "originators" – because we want to explore the (popular) notion that the crises originated in these countries spread into what was then called the ***"Tequila Effect***" and the ***"Asian Flu,"*** respectively.[8] We refer to the other three countries -- Argentina, Chile and Brazil – as ***"potential recipient countries"***. Testing whether volatility states were (statistically) related across "originator" and "recipient" countries is indeed the purpose of this section.

Suppose then that we have two series (countries), with two volatility states. In this bivariate formulation, the number of states is four. For instance, with Mexico and Argentina in a system, we have the following four primitive states, s_t*:

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[7] Edwards (1998) finds evidence of "volatility spillovers" among Mexico, Argentina and Chile. This finding seems to confirm a positive correlation of high variances in international stock markets.

[8] Of course the Asian crisis could be dated a bit earlier, with the collapse of the Thai Baht. However, as the data in Figures 3 through 7 clearly show, no country in our sample suffered increase instability until the

s_t*=1: Mexico - Low volatility, Argentina- Low volatility.

s_t*=2: Mexico - Low volatility, Argentina- High volatility.

s_t*=3: Mexico - High volatility, Argentina - Low volatility.

s_t*=4: Mexico - High volatility, Argentina - High volatility.

The system can be written as:

(4) $\mathbf{r_t} = A + B\,\mathbf{r_{t-1}} + \mathbf{e_t}, \ \mathbf{e_t}|I_{t-1} \sim N(0,\mathbf{H}_t),$

where $\mathbf{r_t} = [r^x_t, r^y_t]$ is a 2x1 vector of returns, $\mathbf{A} = [a_x, a_y]$ and $B = [b_x, b_y]$ are 2x1 vectors, $\mathbf{e_t} = [e^x_t, e^y_t]$ is a 2x1 vector of disturbances, which follow a bivariate normal distribution, with zero mean and a time varying conditional covariance matrix H_t (for notational convenience, we drop the dependence of H_t on the states of the economy). The conditional covariance matrix $\mathbf{H}_t$ is specified as a constant correlation matrix where the diagonal elements follow an SWARCH process. We allow the correlation coefficient, ρ_{st}, to be state-dependent. That is, we let the correlation coefficient to change with the volatility state of the ***originator*** country. This specification is the one emphasized in the "contagion" literature, see Forbes and Rigobon (1999), where the correlation coefficient between two markets, changes significantly due to an unexpected increased in volatility in an originator country. Note, however, that the specification in (4) also allows the series r^x_t and r^y_t to be related through the non-linearities associated with dependent states.

As it was assumed for the univariate case, the probability law that causes the economy to switch among states is given by a K*=4 state Markov chain, P*, with a typical element given by Prob(s_t* = j|s_{t-1}* = i) = p_{ij}*. For the four state model, some of the p_{ij}*'s are close to zero, in order to get convergence, we treat these parameters as given and equal to zero. This reduces the number of parameters to be estimated. As discussed in Hamilton and Lin (1996), this specification is very general and encompasses different interactions among the volatility states of both countries. That is, the transition probabilities, the p_{ij}*'s, could be restricted to fit different assumptions about the underlying volatility states. For example, focusing on p_{24}*, if the volatility states of Mexico and Argentina are independent, then, p_{24}* =

Hong Kong Dollar was attacked by speculators in late October, 1997.

$p_{12}^{Mex}\, p_{22}^{Arg}$. On the other hand, if the Mexican volatility states are shared by Argentina, then $p_{24}^* = 0$.

Our analysis is in three steps: (1) We first estimate the unrestricted model, together with the smoothed probabilities for the four states $s^*_t=j$ (j=1,2,3,4) described above. We are interested in finding out whether pairs of countries are jointly in the "high-high" volatility state, and more specifically we are interested in determining whether this happens around the time of the currency crises of the 1990s. (2) In the second step we formally test whether the volatility states are independent across pairs of countries. And (3), for those cases where the null hypothesis of independence is rejected, we test whether, when the "originator" is in a high volatility state, the "recipient" is always in the high volatility state. This is a very strong test of "volatility synchronization."

To test the null hypothesis of independent states, we first estimate a bivariate SWARCH model, imposing no restriction on the matrix P*. The log likelihood function of the unrestricted model is denoted as $L(H_A)$. We also estimate the model by imposing the restricted transition probability matrix, P*, with elements such as $p_{14}^*=p_{12}^x\, p_{12}^y$. From this estimation, we keep the log likelihood function of the restricted model, $L(H_0)$. Then, we calculate a Likelihood Ratio test, $LR = -2*(L(H_0)-L(H_A))$. Under the null hypothesis, this test has a χ^2 distribution, with k degrees of freedom, where k is given by the number of additional parameters estimated under the alternative hypothesis.

Figure 8 through 14 display the estimated smooth probabilities corresponding to each of the four s_t^* states described above. Consider, for example, Figure 8 on Mexico and Argentina. The first panel presents the probability that both countries are jointly in a low probability state. The second panel contains the probability of Mexico being in a high state and Argentina in a low volatility state. Panel 3 corresponds to the probability that Mexico is in a low volatility state, and Argentina in a high state. Finally, the fourth panel is the probability that both countries are in a high volatility state. Since we are particularly interested in the transmission of high volatility, in the discussion that follows we focus, mostly, on the fourth panel for each country pair. The results are quite interesting. While there are several instances that Mexico and Argentina are in a high volatility state, this happens only once for the case of Mexico and Brazil (in March 1995). Figure 10 confirms that Chile and Mexico did not jointly experience high volatility states during the so-called "tequila episode" of 1994-1995. There are some spikes in the high-high Mexico-Chile joint probability in later years, but they are few and only in two weeks (in 1997) the probability reached 1. We interpret these joint high-high periods as responding to exogenous events (i.e. the Russian and East Asian crises) jointly affecting both countries.

The estimated smooth probabilities when Honk Kong is the "originator" are in Figure 11 through 14 and are quite interesting. First, and surprisingly perhaps, they show that Argentina and Honk Kong have jointly experienced a high volatility state --i.e., prob(s_t*=4)>0.5-- during a number of periods, going back to 1991. They also show that in the latter part of 1997 Hong Kong and Argentina were jointly in the high volatility state. Second, they show that after the attack on the Hong Kong currency board, Brazil and Hong Kong have experienced short periods of joint high volatility. Throughout 1998, both countries also experienced joint high-high periods. Table 13, on Hong-Kong and Chile is, probably, the most interesting of them all. As may be seen, between 1994 and late 1997 there is no evidence whatsoever of the two countries jointly experiencing high volatility states. And then, in October 1997, the probability of state s_t*=4 jumps to one, and stays there. This quite unusual event is as close as we can think to "contagion". Figure 14 looks at the case of our two originators. As may be seen, we find evidence of joint high volatility only during the east Asian crisis period.

The results obtained from the actual estimation of the bivariate SWARCH models are presented in Tables 5 to 7. These tables contain the estimated SWARCH parameters for each country, state-dependent correlation coefficients. as well as

Note that the correlation coefficients are small and, in general, non-significant. Under the standard analysis of the contagion literature, there would be no relation between the processes of both series. That is, contrary to the visual impression of Table 4, the series are independent, even during exogenous events. Moreover, using the definition of Forbes and Rigobon (1999) we find no contagion nor interdependence. We only find independence. As pointed out above, the model in (4) allows the series r^x_t and r^y_t to be related through the non-linearities associated with dependent states.

In Tables 5 to 7 we investigate the dependence between states. These Tables report the Likelihood Ratio test for the null hypothesis that the volatility states are independent across countries, in each pair. The independence state hypothesis can only be rejected for Mexico-Argentina, Hong Kong-Brazil, and Hong Kong-Chile. That is, even though the correlation coefficient is not significantly different than zero in all states, we find a dependence between the interest rates of these countries. For these three cases we then tested the null hypothesis of *volatility synchronization discussed above.* In Tables 5 and 6, we report these tests. We reject the hypothesis that when the when the "originator" is in a high volatility state, the "recipient" is always in the high volatility state.[9]

IV. Concluding Remarks

In this paper we use weekly interest rate data for a group of Latin American countries to analyze the behavior of volatility through time. For this purpose, we use univariate and bivariate switching ARCH models. We find strong evidence for state-varying volatility during the 1990s in Latin American interest rates. The univariate results indicate that high-volatility episodes are, in general, short-lived, usually lasting from two to seven weeks. Then, we examined the joint behavior of Latin American and Hong Kong interest rates. We find that correlation coefficients are not significant and they are not state dependent. According to the traditional contagion literature, this finding points out that the stochastic processes for interest rates are independent. We find, however, a dependence between the stochastic interest rates processes. For Mexico-Argentina, Hong Kong-Brazil, and Hong Kong-Chile we can reject the null hypothesis of independence. Overall, our results are not overly supportive of "contagion" stories.

[9] We also tested an even stronger version of the high volatility synchronization hypothesis, the common states hypothesis. Under this null hypothesis, both countries share the same volatility states. The common states null hypothesis was rejected in all the cases, with a p-value lower than .0001

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TABLE 1: Univariate Statistics for Percentage Changes in Interest Rates

Series	30-day Argentina ARS	30-day Argentina USD	30-day Brazil BRR	30-day Chile CLP	28-day Mexico MXP	30-day Hong-Kong HKD
Mean	-0.269	-0.040	-0.265	0.242	-.022	-.078
SD	8.876	4.036	9.881	15.077	8.977	11.507
Skewness	0.922	0.445	3.490	-1.325	1.088	1.767
Kurtosis	12.73	7.572	21.636	7.726	4.713	16.99
JB-Normality test	2865.81*	745.58*	5060.45	764.43*	423.32*	5381.35*
LB(12)	35.40*	23.09*	14.06*	60.16*	12.33	39.36*
LBS(12)	36.65*	74.12*	0.49	10.74	62.24*	105.04*
Number of Obs.	420	311	236	276	381*	433

TABLE 2. ESTIMATION OF AR(1)-GARCH(1,1):

$\Delta r_t = a_0 + a_1\, \Delta r_{t-1} + \varepsilon_t,$ $\qquad \varepsilon_t|I_{t-1} \sim N(0,h_t)$

$h_t = \alpha_0 + \alpha_1\, \varepsilon^2_{t-1} + \beta_1\, h_{t-1}$

	ARS	USD	BRR
a_o	-0.745 (3.25)	-0.204 (1.48)	-.0133 (0.04)*
a_1	-0.263 (4.53)	-0.256 (3.90)	-0.217 (0.10)*
α_0	2.563 (2.56)	1.247 (2.71)	0.058 (0.03)*
α_1	0.587 (5.47)	0.457 (3.51)	1.321 (0.25)*
β_1	0.589 (11.30)	0.551 (5.5)	0.395 (0.05)*
Likelihood	-1405.3	-786.08	-289.498
LB(5)	10.98	8.40	6.56
LBS(5)	7.17	3.76	1.00
Hansen-Standardized LR test (simulated 1% critical value)	5.43 (4.36)	6.40 (4.32)	7.69 (2.54)

	CLP	MXP	HKD
a_o	-0.032 (0.04)	-0.244 (0.65)	0.077 (0.25)
a_1	0.061 (0.07)	-0.135 (2.16)	-0.234 (3.25)
α_0	0.041 (0.02)*	6.524 (3.65)	0.699 (0.90)
α_1	0.151 (0.05)*	0.169 (3.75)	0.233 (4.36)
β_1	0.801 (0.05)*	0.763 (18.27)	0.860 (47.52)
Likelihood	-316.13	-1329.3	-1551.02
LB(5)	1.74	5.50	6.75
LBS(5)	7.27	10.75	1.07
Hansen-Standardized LR test (simulated 1% critical value)	2.03 (2.05)	7.49 (4.62)	5.82 (4.15)

TABLE 3. ESTIMATION OF AR(1)-SWARCH(3,1)

$\Delta r_t = a_0 + a_1 \Delta r_{t-1} + \varepsilon_t$, $\varepsilon_t|I_{t-1} \sim N(0,h_t)$
$h_t/\gamma_{st} = \alpha_0 + \alpha_1 \varepsilon^2_{t-1}/\gamma_{st-1}$

	ARS	USD	BRR
a_o	-0.487 (0.20)*	-0.085 (0.11)	-0.087 (0.03)
a_1	-0.193 (0.05)*	-0.271 (0.06)*	0.016 (0.05)
α_0	6.804 (1.14)*	1.633 (0.35)*	0.131 (0.03)*
α_1	0.266 (0.09)*	0.209 (0.11)*	0.068 (0.10)
α_2	....	0.064 (0.08)	....
γ_2	3.841 (0.84)+	6.471 (2.36)+	4.851 (1.26)+
γ_3	35.31 (9.85)++	35.39 (13.70)++	128.51 (87.68)
Likelihood	-1352.4	-753.0	-220.3
Likelihood SWARCH(3,q+1)	-1351.5	-753.0	-220.2
LB(12)	13.57	11.02	3.26
LBS(12)	14.34	4.14	1.62
Likelihood SWARCH(2,1)	-1367.5	-759.1	-230.4
Likelihood SWARCH(4,1)	-1358.9	-752.6	-219.9
Likelihood SWARCH(K,q)-L-t	-1351.6	-751.6	-220.1
Likelihood -mean only- K=3	-1435.3	-795.2	-318.4
Likelihood -mean and var.- K=3	-1366.1	-752.3	-222.1

	CLP	MXP	HKD
a_o	0.002 (0.02)	-0.522 (0.27)*	0.171 (0.22)
a_1	0.160 (0.07)*	0.066(0.04)	-0.144 (0.05)
α_0	0.189 (0.03)*	9.284 (2.54)*	9.064 (1.25)
α_1	0.429 (0.13)*	...	0.012 (0.05)
γ_2	3.068 (1.62)	3.971 (1.10)+	7.671 (1.31)+
γ_3	20.957 (11.51)	25.475 (8.02)++	79.168 (24.89)++
Likelihood	-288.7	-1287.0	-1441.6
Likelihood SWARCH(3,q+1)	-288.7	-1286.8	-1441.4
LB(12)	10.50	7.14	6.78
LBS(12)	2.74	40.94*	1.17
Likelihood SWARCH(2,1)	-290.2	-1294.9	-1484.1
Likelihood SWARCH(4,1)	-288.0	-1283.5	-1436.3
Likelihood SWARCH(K,q)-L-t	-288.6	-1281.9	-1430.3
Likelihood -mean only- K=3	-358.1	-1362.2	-1651.9
Likelihood -mean and var.- K=3	-296.2	-1295.8	-1446.7

TABLE 4: IDENTIFYING HIGH VOLATILITY EPISODES AROUND MAJOR CURRENCY CRISES: December 1994-April 1999

	MEX CRISIS 12/30/94	ASIAN CRISIS 10/24/97	RUS CRISIS 9/04/98	BRAZ CRISIS 1/15/94
ARGENTINA	3/10/95 (5)	10/31/97 (6)	8/28/98 (5)	1/15/99 (5)
BRAZIL	3/10/95 (1)	10/31/97 (1)	9/11/98 (1)	1/15/99 (1)
CHILE	xxx	3/06/98 (2)	9/04/98 (4)	2/05/99 (3)
MEXICO	12/30/94 (25)	10/24/97 (7)	9/04/98 (5)	xxx
HONG KONG	1/13/95 (2)	10/24/97 (52)		xxx

Notes:
Each entry provides a starting date for the high volatility state (3rd state) and the number of weeks the economy was in the high volatility state during each crisis. xxx means the economy was not in the 3rd state during the given crisis.

TABLE 5: MEXICO ORIGINATOR: SWARCH(2,1) BIVARIATE SYSTEM

	Coefficients (Standard errors)		
	Receptor ARS	Receptor BRR	Receptor CLP
$a_{M,o}$	-0.639 (0.31)*	-1.169 (0.43)*	-0.815 (0.36)*
$a_{M,1}$	-0.089 (0.05)	0.070 (0.04)	-0.061 (0.05)
$\alpha_{M,0}$	20.262 (3.49)*	20.734 (14.85)	17.093 (4.65)*
$\alpha_{M,1}$	0.001 (0.08)	0.001 (0.49)	0.001 (0.08)
$\gamma_{M,2}$	9.719 (1.88)+	14.595 (3.69)+	17.093 (3.43)+
$a_{Rec,o}$	0.553 (0.23)*	0.090 (0.04)*	-0.012 (0.04)*
$a_{Rec,1}$	0.215 (0.06)*	0.124 (0.06)*	0.117 (0.07)
$\alpha_{Rec,0}$	11.193 (1.49)*	0.231 (0.03)*	0.245 (0.03)*
$\alpha_{Rec,1}$	0.262 (0.08)*	0.110 (0.09)	0.347 (0.11)*
$\gamma_{Rec,2}$	10.739 (5.38)+	31.35 (11.74)+	7.512 (2.13)+
ρ_{M-LV}	0.091 (0.07)	0.095 (0.12)	0.008 (0.09)
ρ_{M-HV}	0.190 (0.10)	0.170 (0.18)	-0.108 (0.12)
Likelihood SWARCH	-2481.1	-1025.8	-1231.4
Likelihood-independent state	-2488.9	1029.1	-1233.5
LR-independent states (p-value)	14.4 (.0485)	6.6 (.580)	5.0 (.625)
Likelihood-high volatility syncrhon.	2491.6	....	...
LR-high volatility syncrhon. (p-value)	21.0 (.0018)		

TABLE 6: HONG KONG ORIGINATOR: SWARCH(2,1) BIVARIATE SYSTEM

	Coefficient (Standard Error)		
	Receptor ARS	Receptor BRR	Receptor CLP
$a_{HK,o}$	0.285 (0.25)	0.035 (0.25)	0.194 (0.24)
$a_{HK,1}$	-0.241 (0.07)*	0.232 (0.06)*	-0.15 (0.04)*
$\alpha_{HK,0}$	12.628 (3.49)*	7.948 (1.00)*	9.301 (1.09)*
$\alpha_{HK,1}$	0.197 (0.09)*	0.001 (0.09)	0.001 (0.09)
$\gamma_{HK,2}$	20.09 (3.23)+	54.058 (10.32)*	49.520 (9.23)+
$a_{Rec,o}$	-0.583 (0.24)*	-.085 (0.03)*	-0.021 (0.04)
$a_{Rec,1}$	0.173 (0.05)*	0.132 (0.05)*	0.118 (0.07)
$\alpha_{Rec,0}$	13.791 (2.18)*	0.225 (0.34)*	0.245 (0.04)*
$\alpha_{Rec,1}$	0.391 (0.10)*	0.113 (0.09)	0.348 (0.11)*
$\gamma_{Rec,2}$	11.955 (2.48)+	36.396 (14.28)+	7.349 (2.11)+
ρ_{H-LV}	0.119 (0.08)	-0.057 (0.09)	-0.046 (0.08)
ρ_{H-HV}	0.069 (0.09)	0.142 (0.10)	-0.0957 (0.11)
Likelihood SWARCH	-2802.3	-989.7	-1168.1
Likelihood-independent state	-2806.7	997.3	-1174.3
LR-independent states (p-value)	7.2 (.3594)	15.2 (.0096)	12.4 (.0350)
Likelihood-high volatility syncrhon.	....	1024.8	1172.0
LR-high volat. syncrhon. (p-value)		70.2 (<.0001)	7.9 (.0193)

TABLE 7: HONG KONG AND MEXICO- SWARCH(2,1) BIVARIATE SYSTEM

	Coefficient
$a_{H,o}$	0.185 (0.24)
$a_{H,1}$	0.241 (0.06)*
$\alpha_{H,0}$	12.605 (1.73)*
$\alpha_{H,1}$	0.246 (0.10)
$\gamma_{H,2}$	25.498 (4.48)+
$a_{M,o}$	-0.705 (0.30)*
$a_{M,1}$	-0.072 (0.04)
$\alpha_{M,0}$	17.541 (4.10)*
$\alpha_{M,1}$	0.001 (0.10)
$\gamma_{M,2}$	11.727 (2.32)+
$\rho_{M\text{-}LV}$	0.003 (0.07)
$\rho_{M\text{-}HV}$	0.048 (0.10)
Likelihood SWARCH	-2573.0
Likelihood-independent states	-2576.6
LR-independent states (p-value)	7.2 (.5152)

Figure 1:
Nominal Interest Rates in Selected
Latin American and East Asian Countries:
First Differences (Weekly Data, 1994-1999)

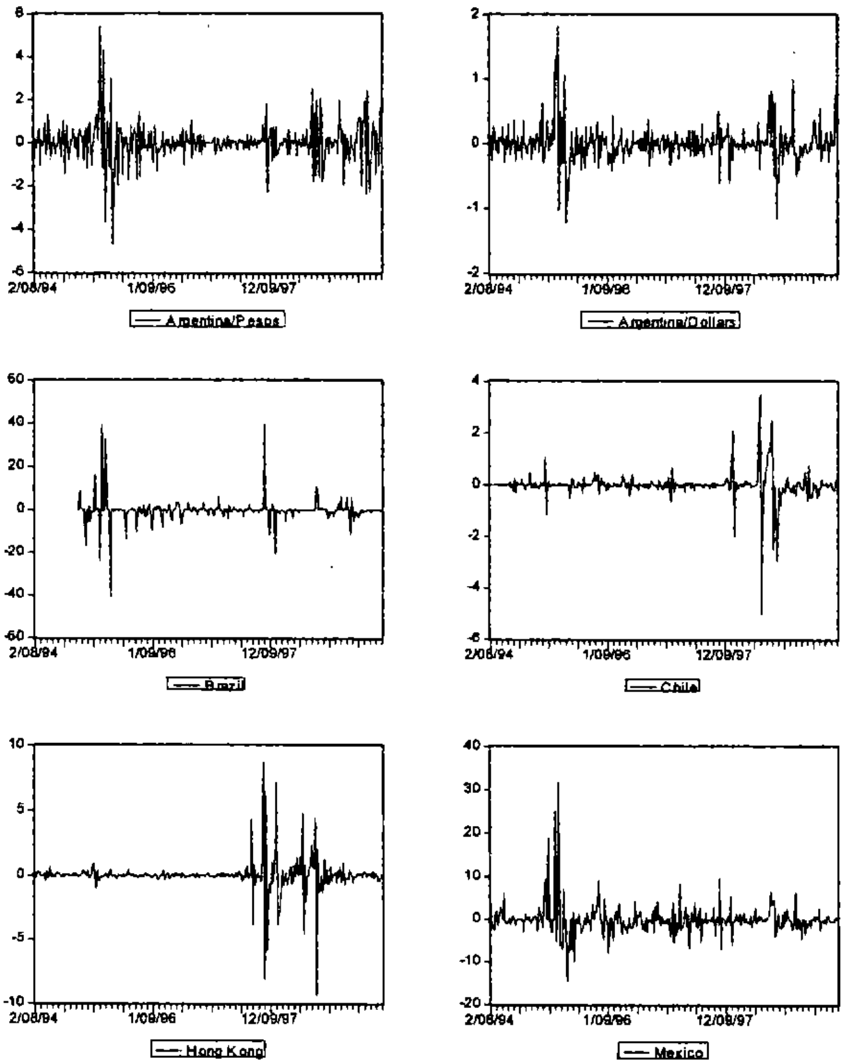

Figure 2:
Interest Rates in Selected Emerging Countries:
Levels
(Weekly Data: 1994-1999)

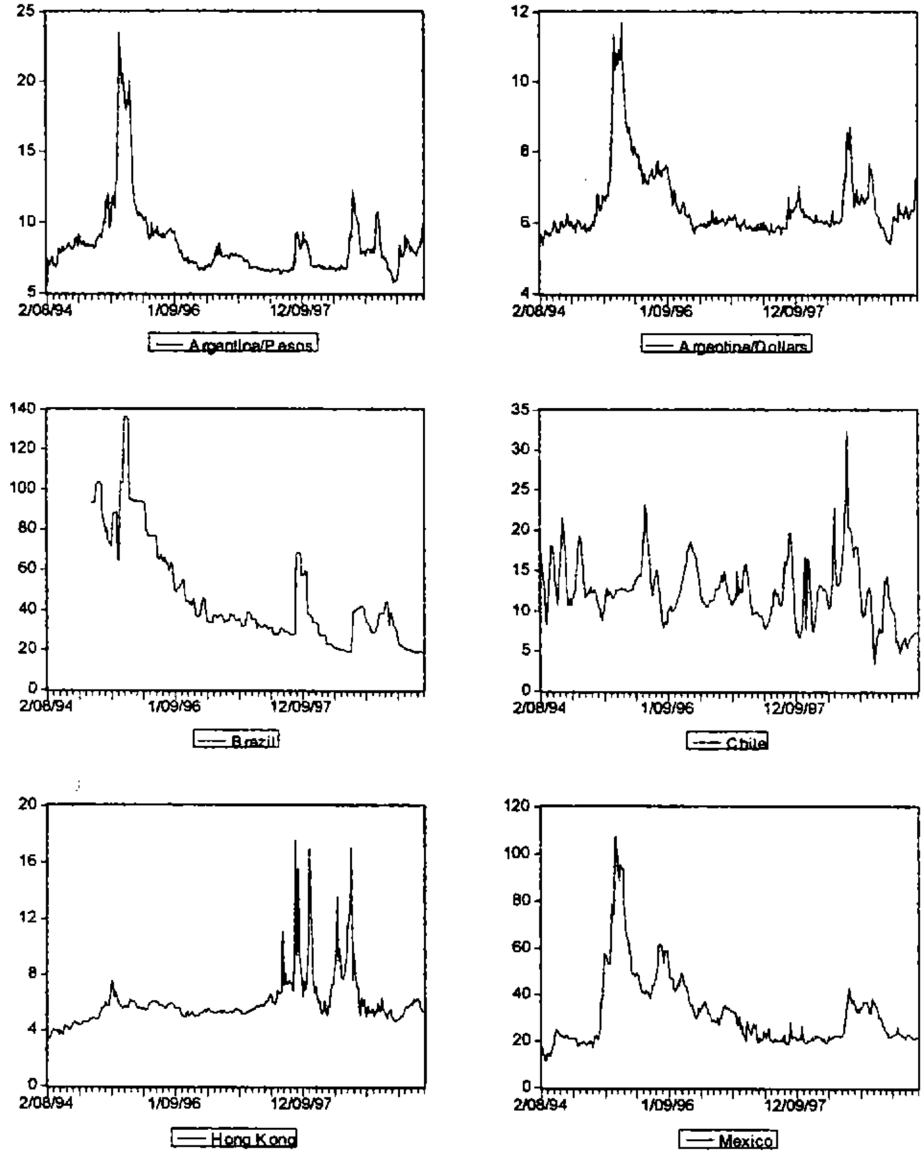

Figure 3:
SWARCH (3,1) Estimates for Argentina Peso Denominated Interest Rates

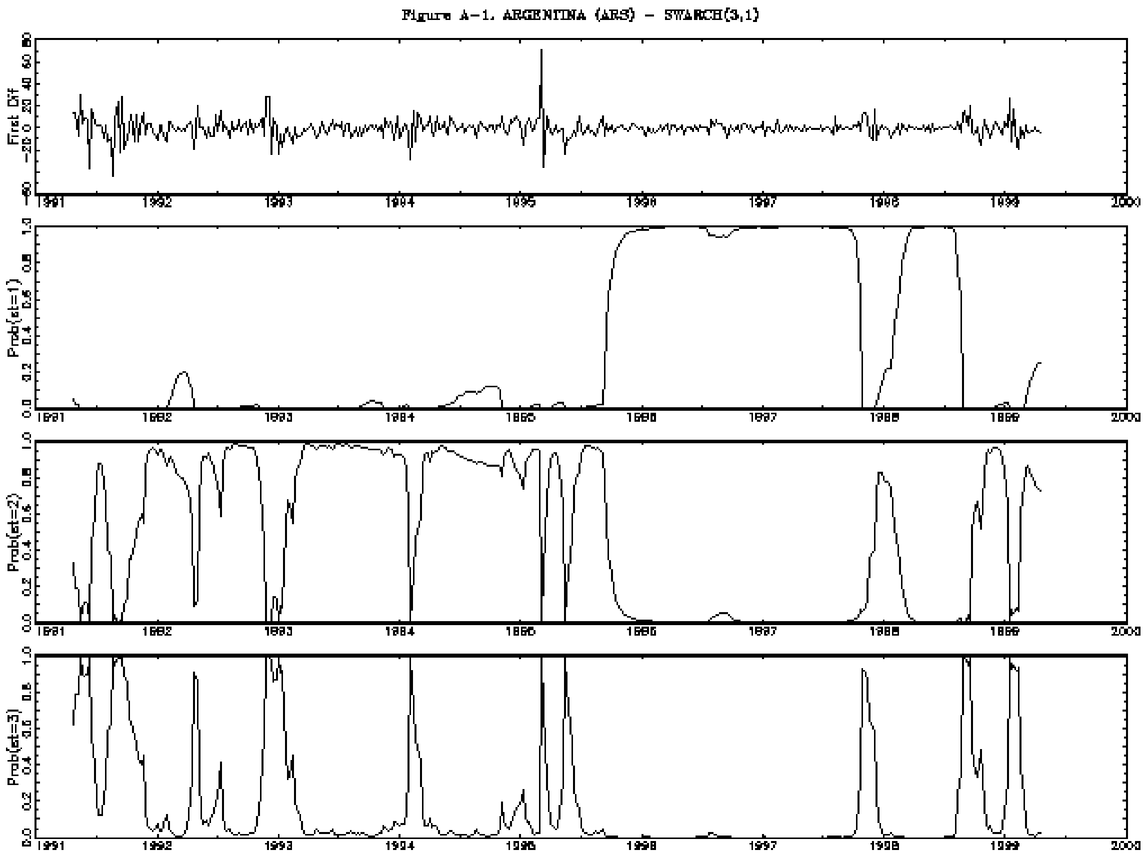

Figure 4:
SWARCH (3,1) Estimates for Brazil Nominal Interest Rates

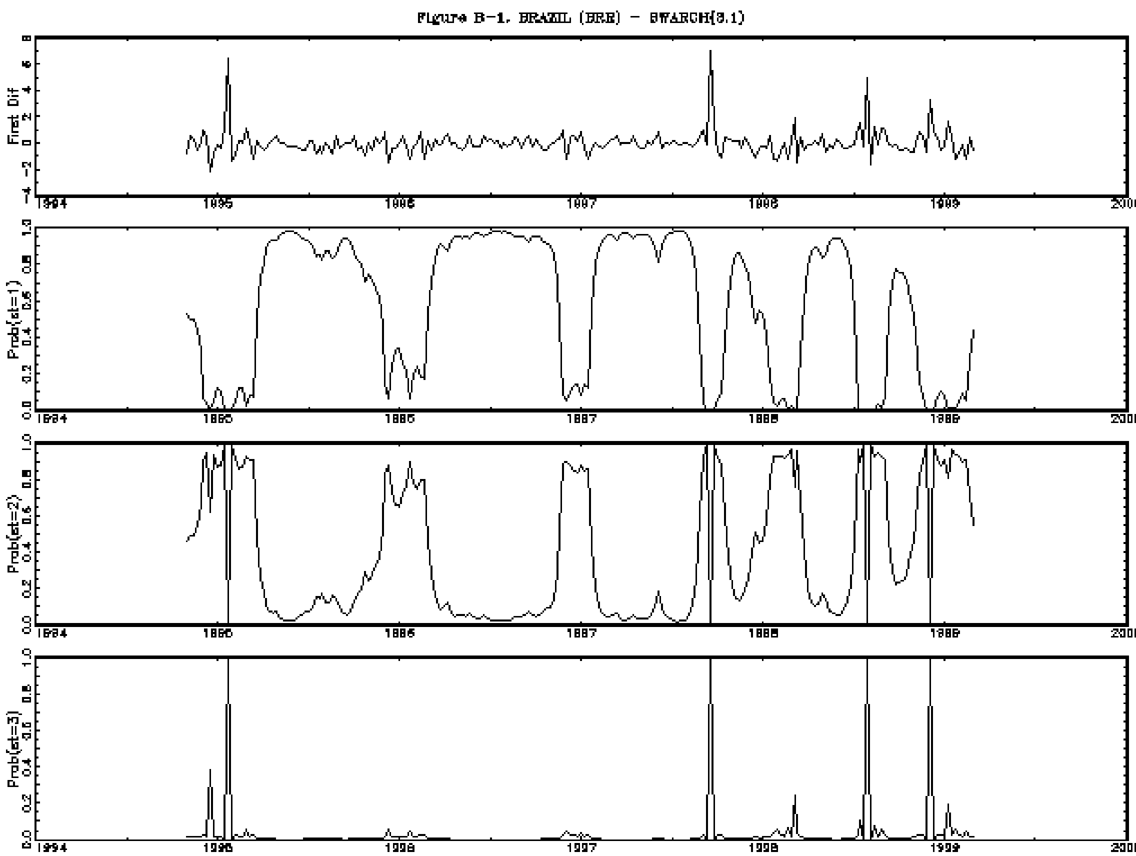

**Figure 5:
SWARCH (3,1) Estimates for Chile Nominal
Interest Rates**

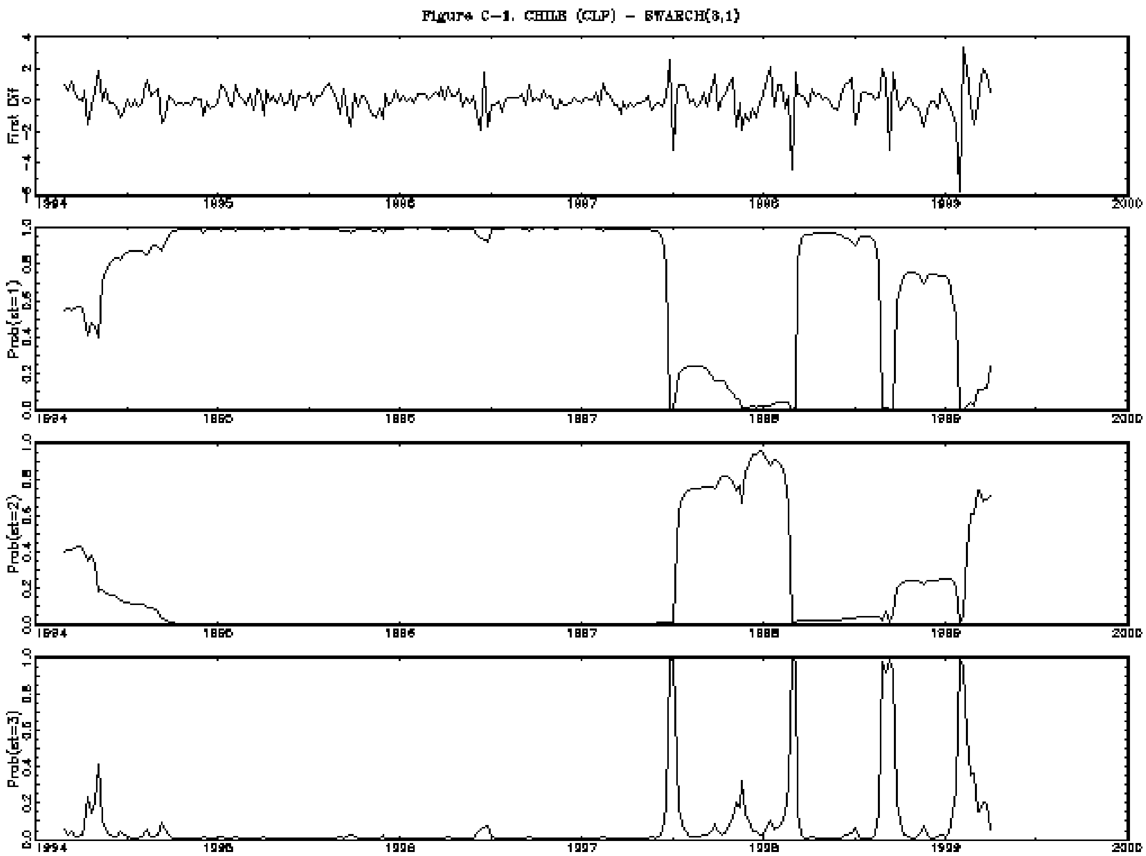

Figure 6:
SWARCH (3,1) Estimates for Hong Kong Nominal Interest Rates

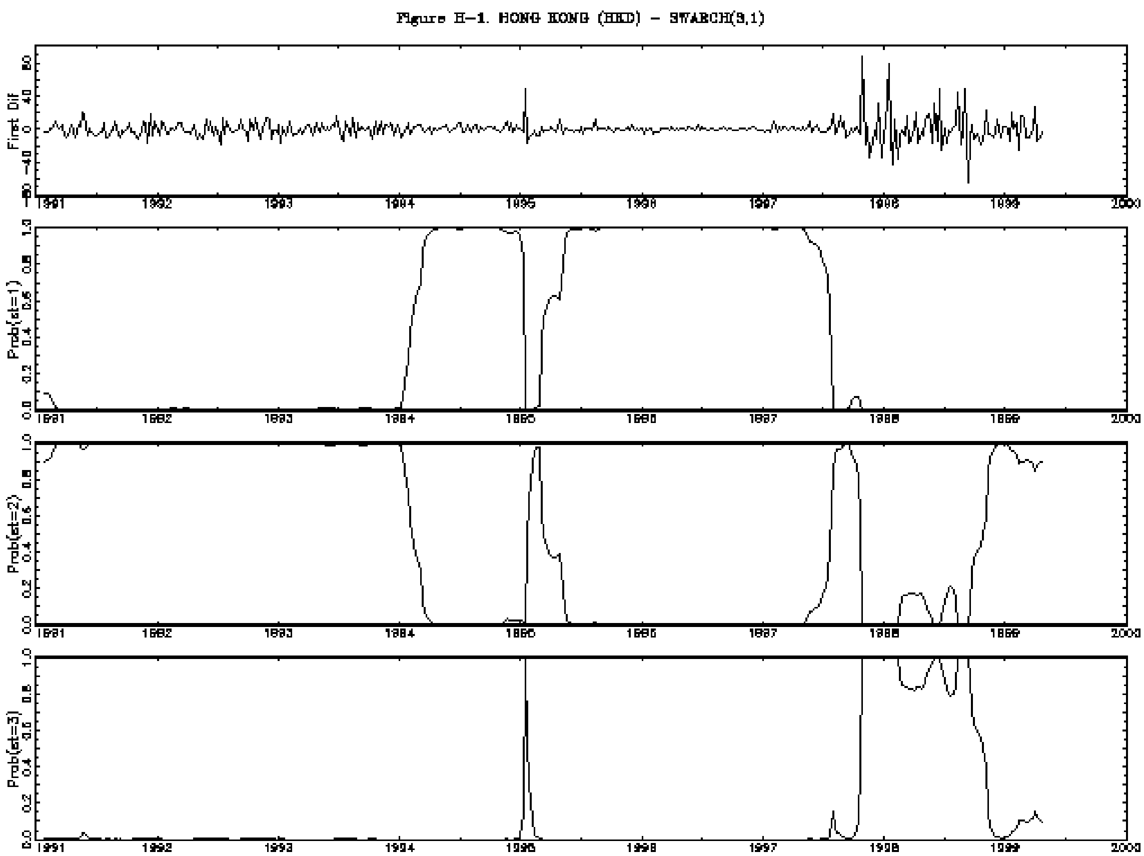

Figure 7:
SWARCH (3,1) Estimates for Mexico Nominal Interest Rates

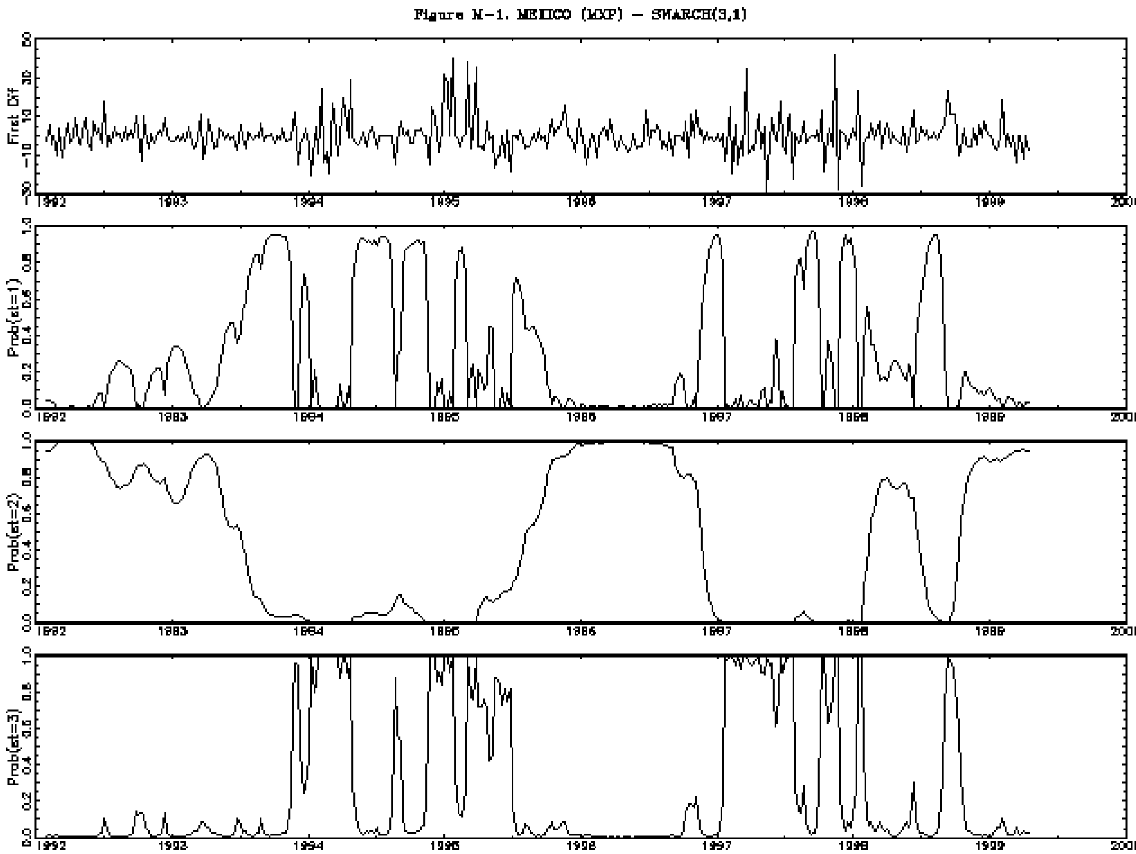

Figure 8
Bivariate SWARCH Model:
Mexico-Argentina

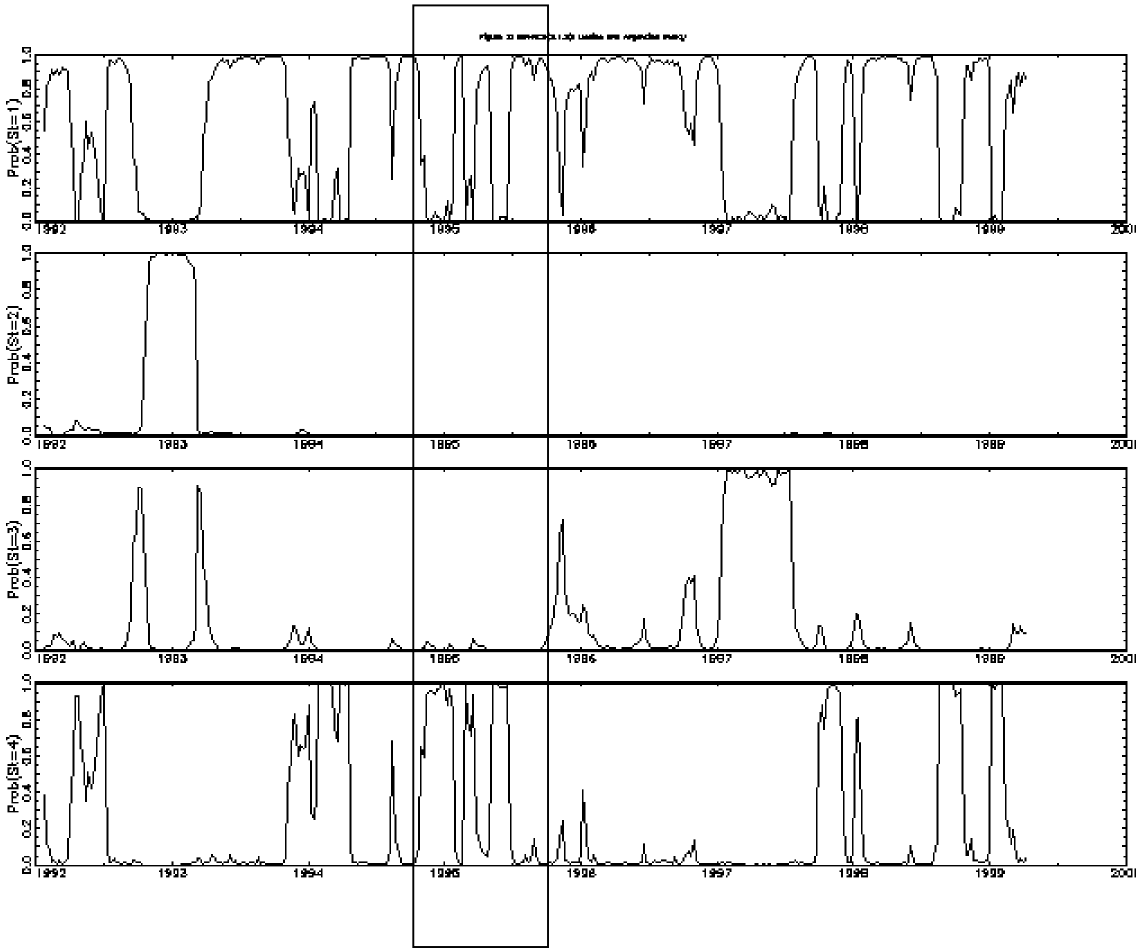

Figure 9
Bivariate SWARCH Model:
Mexico-Brazil

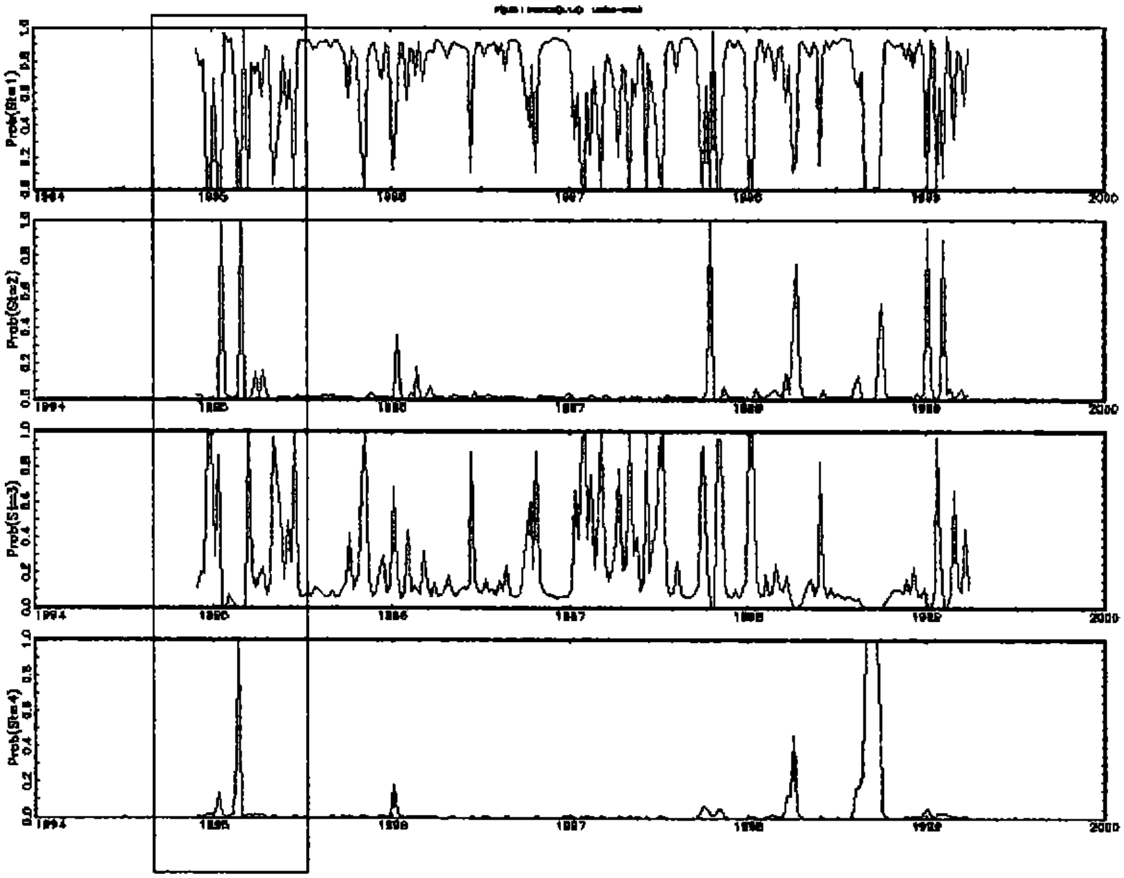

Figure 10
Bivariate SWARCH Model:
Mexico-Chile

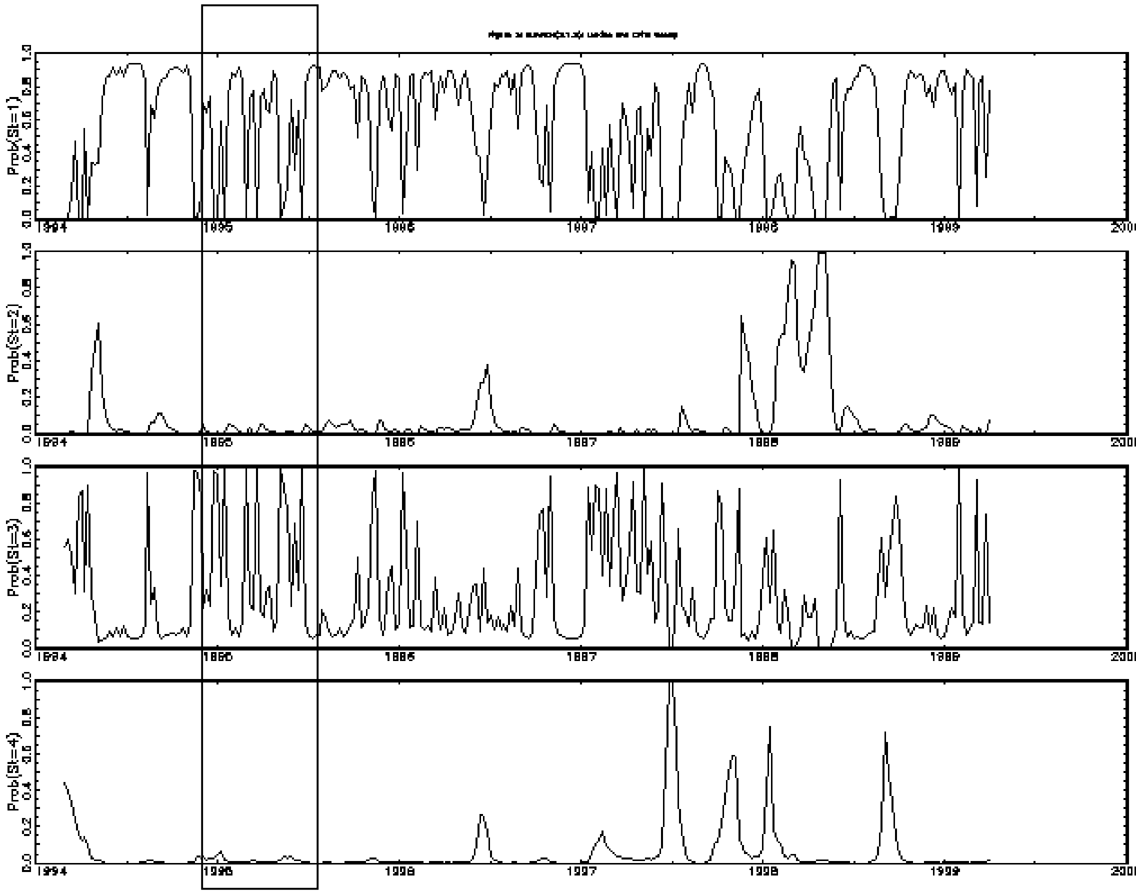

Figure 11
Bivariate SWARCH Model:
Hong Kong-Argentina

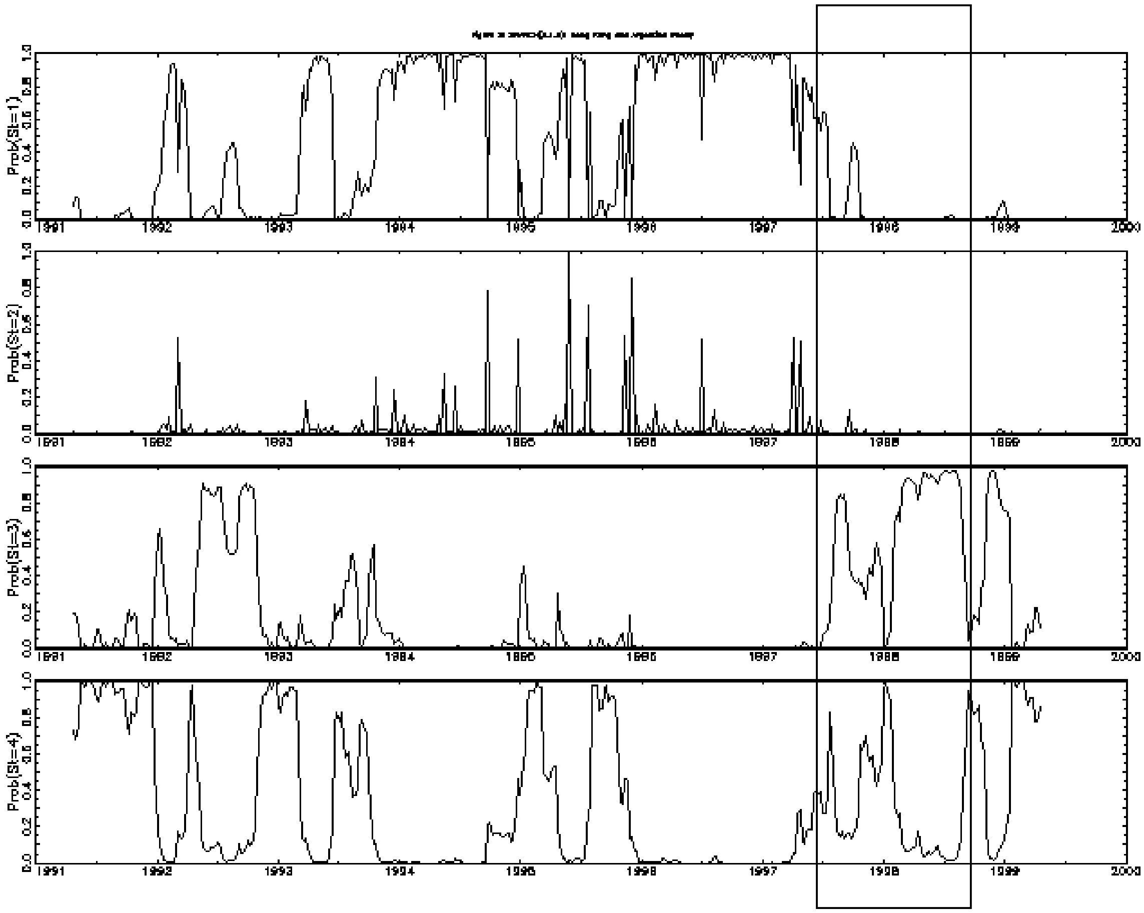

Figure 12
Bivariate SWARCH Model:
Hong Kong-Brazil

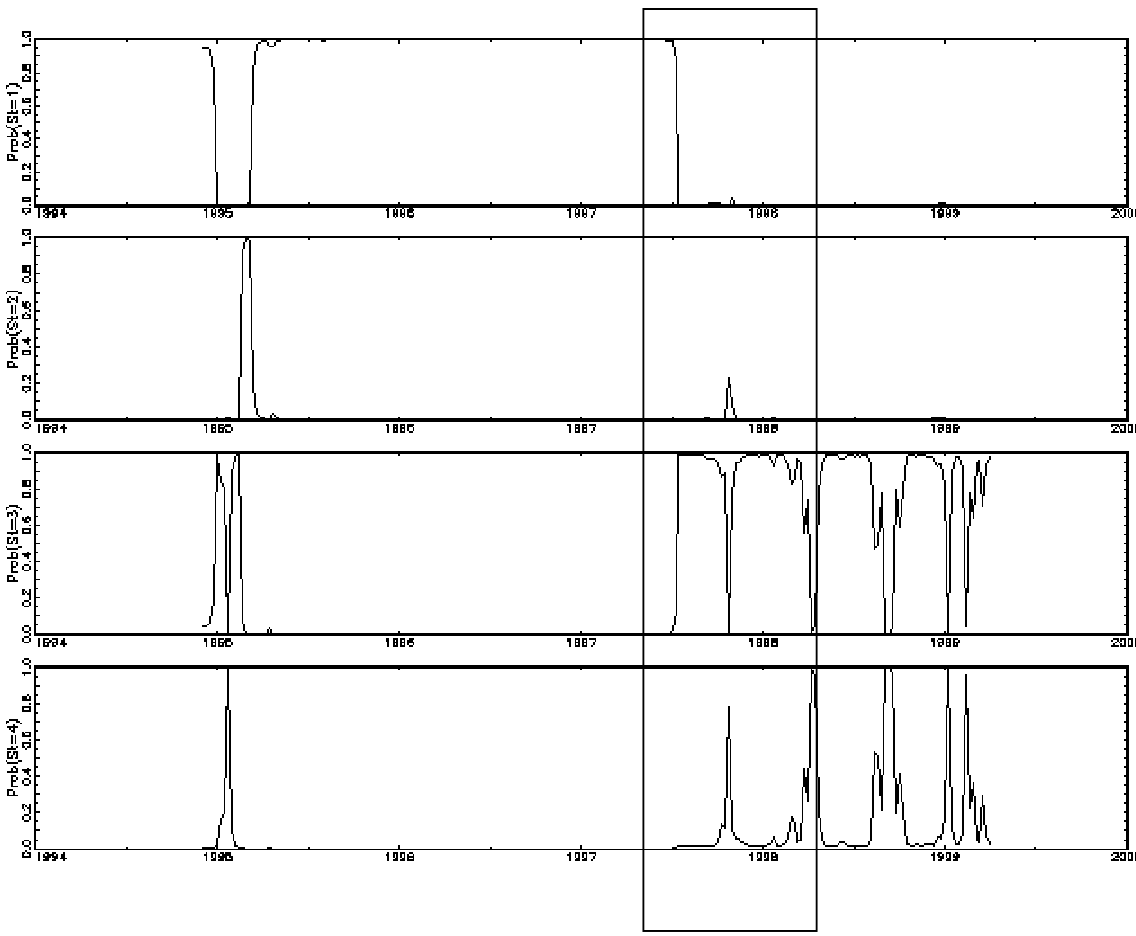

Figure 13
Bivariate SWARCH Model:
Hong Kong-Chile

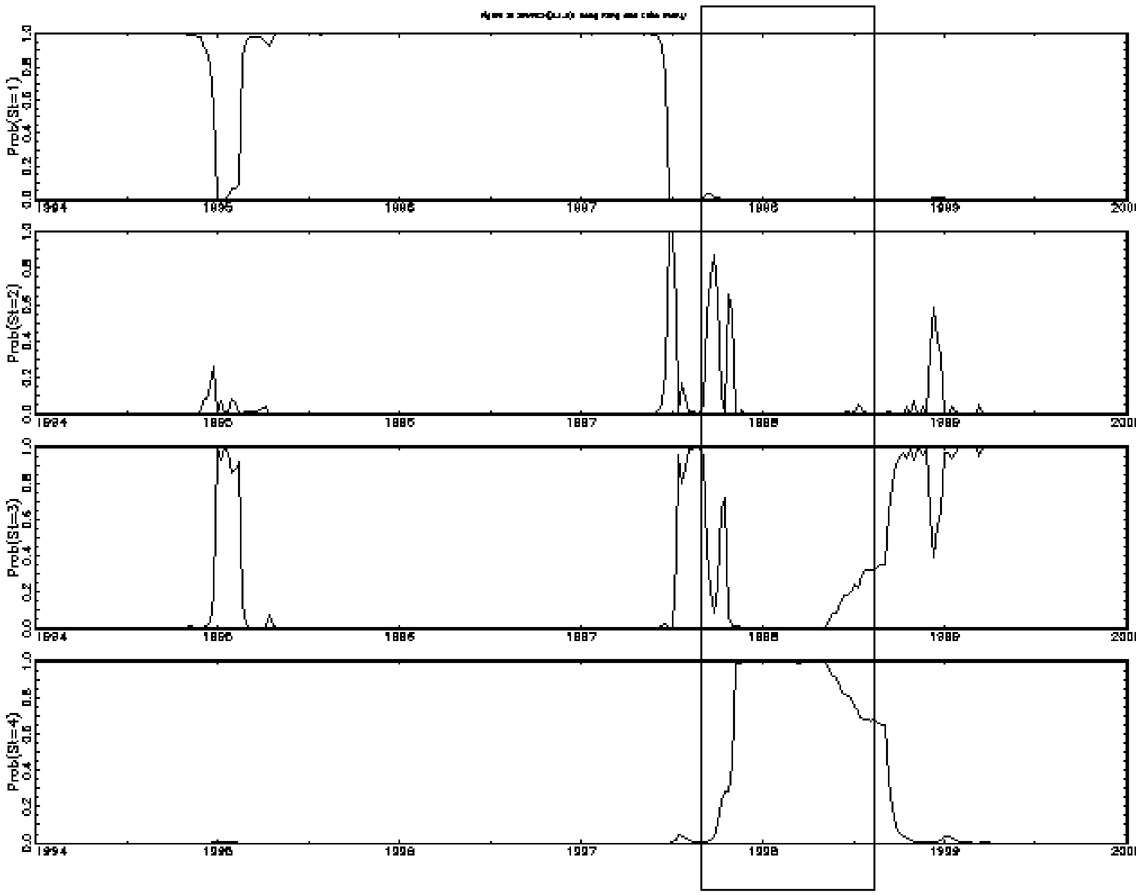

Figure 14
Bivariate SWARCH Model:
Hong Kong-Mexico