Volatility Dependence and Contagion in Emerging Equity Markets

by

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ABSTRACT

In this paper we use weekly stock market 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 in one market are correlated with periods of high volatility in other countries. The analysis uses both on univariate and bivariate switching volatility models. Our results do not rely on the correlation coefficients, but on the co-dependence of volatility regimes. The results indicate that high-volatility episodes are, in general, short-lived, lasting from two to twelve weeks. We find strong evidence of volatility co-movements across countries, especially among the Mercosur countries. Overall, our results are not overly supportive of "contagion" stories.

I. Introduction

During the last decade financial markets have become increasingly integrated in the world economy. This trend, which has affected both advanced an emerging countries, has largely been the result of deliberate policies aimed at reducing financial "repression" and liberalizing national capital markets --see The World Bank (1997). In the aftermath of the East Asian and Russian crises of the 1990s a number of authors have argued that this increase in the degree international of capital mobility has gone too far, creating a higher degree of financial instability among emerging countries. More specifically, it has been argued that in world with a high degree of capital mobility financial instability will be transmitted across nations. This, in turn, will have negative effects on investment and growth. A particularly startling characteristic of the second half of the 1990s is that international turmoil seems to be transmitted across countries that appear to be largely unrelated. A number of authors have referred to this phenomenon as "contagion" --see Edwards (2000).

In this paper we use weekly stock market data from a group of Latin American and Asian countries to investigate two issues: First, we analyze whether the degree of financial instability has indeed increased during the last several years. Second, we investigate whether periods of increased stock market volatility coincide across countries. Understanding these issues has a number of important policy implications. Indeed, supporters of the imposition of capital controls have largely based their views on the notion that periods of financial instability are transmitted across countries --see Stiglitz (1999).

We address these issues 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 of stock market returns. A particular attractive feature of this approach is that it allows us to date periods of unusually high volatility. We find that, although the degree of volatility does change through time, it has not experienced, in any of our countries, a secular increase. Our results indicate that in most (but not all) countries the "unusually high volatility states" are short-lived. We also find that these periods of "high volatility" tend to roughly coincide across some countries.

Our analysis departs from other work in the area in that we use multivariate extension of the SWARCH model to explore whether there are co-movements in stock market volatility across countries. This type of analysis is particularly important in current debates on financial "contagion" across countries. Indeed, the existence of statistically significant comovements in volatility can be interpreted as providing some evidence regarding the presence of contagion. In particular, a simultaneous increase in the (conditional) variance of stock returns would have important implications for the interpretation of traditional models of contagion, based on detecting break-points in simple returns correlations across countries --see Forbes and Rigobon, (1999).

Since multivariate SWARCH models are highly intensive in computing time, in this paper we restrict its application to pairs of countries. The bivariate SWARCH model allows for dependence not only through the correlation coefficient, but also through the Markov matrix, which determines the states. We find evidence for state-dependent correlations, where the states tend to be related to international crises. During high volatility periods due to international crisis, correlations among Latin American emerging markets increase between two to four times. We also find strong evidence of volatility dependence among all Latin American markets. We also find, however, that Hong Kong, which we take as an emblematic representative of the Asian financial crisis of 1997, does not show a non-linear state dependence, with Chile and Brazil.[1]

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). 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.

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[1] In a companion paper we use data for all five countries to analyze "volatility comovements" in domestic interest rates. See Edwards and Susmel (2000).

II. Equity Returns in the 1990s: Preliminary Data Analysis

Our analysis deals with weekly equity returns, denominated in U.S. dollars, for Argentina, Brazil, Chile, Hong Kong and Mexico during the 1990s. The data were taken from the Morgan Stanley Capital International data set. In Table 1 we present summary statistics for the stock returns of our five national stock markets. 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. In the analysis that follows in Sections III and IV we are interested in understanding in detail the nature of stock market volatility in these five countries. In particular, we analyze whether there have been changes in the statistical processes generating volatility. More specifically, we are interested in investigating whether there has been a trend towards higher stock market volatility in these markets. We also use our data set to inquire whether high volatility states coincide across countries.

III. Stock Returns Volatility and Breakpoints: Univariate Analysis

III.1 The Model

Most studies on stock returns volatility are based on the estimation of GARCH-type models, see 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, or other international financial crises, among other. In this paper we use a variant of 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) $\Delta r_t = a_0 + a_1 \Delta r_{t-1} + \varepsilon_t$, $\varepsilon_t | I_{t-1} \sim N(0,h_t)$

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

where r_t is the log of the stock market index, and 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 it is possible to 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 analyst/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. The results, which are reported in Table 2 finds significant ARCH effect for all the series. Moreover, 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 tends to be unusually high for high frequency financial time series. Also, for Chile β_1 is unusually low. Moreover, for most countries the sum of α_1 and β_1 is close to one, which makes shocks to the conditional variance highly 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 the statistical process generating the 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 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 1% level. For example, the Hansen test for Chile’s returns provides a standardized likelihood ratio test of 3.07, which is higher than the simulated 1% upper bound critical value of 2.88.

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[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

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

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. 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.

After rejecting the hypothesis of no-regime switch, the next step is to use the (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. Since we are interested in bivariate switching results, and three states considerably complicate the bivariate estimation, we focus our attention to a two-state system. Our results suggest, however, that for some countries a three-state SWARCH models may be appropriate[4]. The results obtained are reported in Table 3. Several interesting findings emerge from this table. First, the switching parameters, the γ_i's, are significantly different than one in all series. That is, for each of our five national stock markets it is possible to distinguish a ***"low,"*** 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 or disappear. Three, with the exception of Chile, 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) show, 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 two-states case, γ_2 provides information on how much higher is high volatility relative to low volatility. For example, in one extreme, for Argentina's stock returns the high volatility state is on average around ten times higher than that in the low volatility state. On the other hand, for Hong Kong the high volatility state is on average around five times higher than that in the low volatility state.

The basic results obtained from our bivariate analysis are summarized in Figures 1 through 5. Consider first Figure 1. The top panel presents plots the Argentinean weekly stock returns. 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 (high volatility) at time t. The observations are classified following Hamilton's (1989) proposed method for dating

[4] Standard likelihood ratios reject, with the exception of Mexico, the null hypothesis 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. Interestingly enough, our analysis on domestic interest rates in these five countries suggests that a three-states representation is more adequate for interest rates.

regime switches. According to this procedure, an observation belongs to state i if the smoothed probability Prob(s_t=i|r_T,r_{T-1},...,r_{-3}) is higher than 0.5. According to Figure 1 stock market returns in Argentina switch between the low volatility state and the high volatility state during the first four years of the sample. Then, from 1993 on, Argentinean stock returns tend to have long stays in the low volatility state. Only during the Mexican (late 1994), Asian (late 1997), Russian (August-September 1998) and Brazilian (January 1999) crises, stock returns switched to the high volatility state. Figure s 2 to 5 present similar graphs for Brazil, Chile, Mexico and Hong Kong. In general, we observe a similar behavior than for the Argentinean case.

A particularly interesting feature of the results in Figures 1 to 5 is that, at a first glance, it appears that since late 1994 the stays of the stock returns for Latin American stock market returns in the high volatility state correspond (roughly) to foreign (exogenous) events. Indeed, the analysis of the figures indicate that after 1994 shifts to the high volatility state tend to coincide with the Mexican crisis, the Asian crisis, the Russian crisis, and the Brazilian crisis, respectively. These results may suggest that indeed emerging markets were 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 before 1994 cannot be attributed –or at least nor easily– to external events.

In order to have a better understanding of the periods of high volatility, we estimated, for each of our five countries, a three state SWARCH model. We label the third state as "unusually high volatility." In Figures 6, we present the smoothed probabilities of the "unusual" third state for the five national stock markets. As may be seen there is a remarkable correspondence for the "unusually high volatility spikes" in a number of our countries. More specifically, the following characteristics of our results emerge from this figure:

(1) All four Latin American countries exhibit a spike in late 1994. This corresponds to what has come to be known as the "tequila effect" crisis. As we expected, Mexico – the country where the 1994 currency crisis– was the first Latin American country to experience, at this time, a shift to the "unusually high volatility" state.

(2) Volatility of stock market returns in Hong-Kong did not experience an increase at the time of the "tequila crisis." Interestingly, this contrasts with the behavior of nominal

domestic interest rates analyzed by Edwards and Susmel (2000). These authors found that in January 1995, and for a period of two weeks, Hong Kong's domestic interest rates moved to a state of "unusually high volatility."

(3) In four of the countries in the sample there are "unusually high volatility spikes" in late 1997, at the time the Hong Kong currency board came under attack by speculators. The only exception is Chile. Notice, however, from Figure 3 that at that time Chile did shift from the "low" to the "high" volatility states.

(4) Four of the countries experienced a shift to the "unusually high volatility state" in August-September 1998, when Russia devalued the rubble and defaulted on its debt. Chile is, once again, the exception: while (as Figure 3 shows) Chile moved to high volatility, it did not go all the way to the highest volatility state.

(5) Finally, Argentina, Brazil and Mexico experienced a shift in volatility to the "unusually high state" in January 1999, when Brazil devalued the real and entered into a (short-lived) crisis.

A particularly interesting feature of the results reported in Figure 6 is that for Hong Kong and Chile, countries with a history of credible economic policies, the unusual volatility periods are few and do not last more than two weeks. Indeed, the relative long stays in the unusual volatility state and the relative high occurrence of unusual volatility for Argentina, Brazil and Mexico are likely to reflect a low degree of credibility enjoyed by the government economic policies, especially in the period before 1994.[5]

Table 4 contains a summary of our findings on the extent and duration of unusual volatility in the periods surrounding the Mexican, East Asian, Russian and Brazilian currency crises of the 1990s, already presented in Figure 6. 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 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

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

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 stock market volatility switches across countries during the second half of the 1990s. In this section, we explore this issue further by developing a bivariate switching volatility model.[6] We take advantage of the Markov process by the Hamilton (1989) filter to test whether volatility states are *independent* across countries. Generally speaking, markets are *independent*, if financial markets across countries are segmented. If, however, financial markets are highly integrated –as most authors believe to be the case since, at least, the mid 1990s–, shocks will be transmitted rapidly across countries, and 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 restrict our analysis to the case of two countries and two volatility states (high volatility and low volatility). That is, we estimate a bivariate SWARCH model.

In order to organize the discussion, and reduce the dimensionality of the problem, we concentrate on the cases of Mexico and Hong-Kong. More specifically, we investigate whether it is possible to reject thew hypotheses that the volatility processes are independent in the following pairs of countries:

(a) Mexico-Argentina, Mexico-Brazil, Mexico-Chile;

(b) Hong Kong-Argentina, Hong Kong-Brazil, Hong Kong-Chile;

(c) Hong Kong-Mexico.

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[6] 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.

This already gives us seven two-country combinations. We have focused 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.[7] We refer to the other three countries -- Argentina, Chile and Brazil – as ***"potential recipient countries"***. Given the importance of Brazil for the Mercosur nations, we also use Brazil as a potential originator and Argentina and Chile as potential recipients. 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*:

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, $\mathbf{e_t} = [e^x{}_t, e^y{}_t]$ 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 to be state-dependent. We let the correlation coefficient to change with the volatility state of the ***originator*** country. Later, we relax this assumption. The specification set in equation (4) allows the series $r^x{}_t$ and $r^y{}_t$ to be related through the non-linearities associated with dependent states. $\mathbf{A} = [a_x, a_y]$ and $B = [b_x, b_y]$ are 2x1 vectors.

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

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 $\text{Prob}(s_t^* = j|s_{t-1}^* = i) = p_{ij}^*$. 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, $p_{24}^* = p_{12}^{Mex}\, p_{22}^{Arg}$. On the other hand, if the Mexican volatility states are shared by Argentina, then $p_{24}^* = 0$.

Our bivariate 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 two volatility synchronization hypothesis: (a) In the first one we test whether, when the "originator country" is in a high volatility state, the "recipient country" is ***always*** in the high volatility state. We call the behavior under this hypothesis *"high volatility synchronization."* (b) In our second test we inquire whether when the "originator country" is in a low volatility state, the "recipient country" is always in the low volatility state. We call the behavior under this hypothesis *"low 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 7 through 16 display the estimated smooth probabilities corresponding to each of the four s_t* states described above. Consider, for example, Figure 7 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, while Argentina is in a high volatility 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 revealing. While there are several instances that Mexico and Argentina are in a high volatility state, this only happens after 1994, and it tends to happen only at the time when there are major international crises. In general, the same behavior is observed for the cases of Mexico and Brazil (Figure 8), and Mexico and Chile (Figure 9). We interpret these joint high-high periods as responding to exogenous events (i.e. the Mexican, Asian, Russian and Brazilian crises) jointly affecting both countries.

The estimated smooth probabilities when Brazil is the originator for the other two Mercosur countries, Argentina and Chile, are shown in Figure 10 and 11, respectively. These Figures show that during all international crises Brazil, Argentina and Chile share the same high volatility state. Interesting , the second state (Brazil low volatility and the other country high volatility) is not very well defined and does not show persistence. That is, when Brazil is in the low volatility state the other Mercosur partner does not stay long in the high volatility state.

The estimated smooth probabilities when Honk Kong is the "originator country" are in Figure 12 through 15 and are also quite interesting. First, and surprisingly perhaps, they show that Argentina and Honk Kong 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 –at the time when the East Asian currency crisis was in full swing– Hong Kong and Argentina were jointly in the high volatility state. Figure 15 for Hong Kong and Mexico shows a remarkable similar joint behavior of these countries to Hong Kong and Argentina when Hong Kong is in the high volatility state. Second, these figures also show that after the attack on the Hong Kong currency board in late October, 1997, Brazil and Hong Kong experienced short periods of joint high volatility. Throughout 1998, both countries also experienced joint high-high periods. In contrast, Figures 13 and 14, on Hong-Kong and Brazil, and Hong Kong and Chile respectively, show that some of the joint states are not very well defined.

The results obtained from the actual estimation of the bivariate SWARCH models are presented in Tables 4 to 6. These tables contain the estimated SWARCH parameters for each country, state-dependent correlation coefficients, as well as the Likelihood Ratio test for the null hypothesis that the volatility states are independent across each pair of countries.. In Tables 5 and 6, we present the results for Mexico and Brazil, taken as originator countries. We find strong evidence for state dependent correlations with the originator country, especially with Mexico. In general, our correlation estimates are very close to the ones obtained in the very recent literature on contagion, see Forbes and Rigobon (1999).The correlation coefficient between Mexico and the other Latin American markets jumps between two and four times when Mexico is in the high volatility state. Forbes and Rigobon (1999) argue that under heteroscedastic conditions, the estimates of the correlation coefficient in the high volatility state are biased. The SWARCH model, however, explicitly models heteroscedasticity, and if this is the correct model, our estimators are maximum likelihood estimates. an important difference between our analysis and more traditional results, is that we don't use correlation coefficients to test dependence. Instead our dependence tests are based on the Markov structure of the Hamilton process, as described above.

According to our results the independence state hypothesis can be rejected for all Latin American markets. For the case of the Latin nations in our sample, it is not surprising that the independence hypothesis is rejected, as Argentina, Brazil and Chile are subject to numerous economic interconnectedness and tend to be affected by similar shocks. For these Latin American cases, we then tested the two null hypotheses of *volatility synchronization discussed above.* In Tables 5 and 6, we report these tests. We reject *the "high volatility synchronization"* hypothesis, which states that when the when the "originator country" is in a high volatility state, the "recipient country" is always in the high volatility state. With the exception of the Brazil-Argentina pair, we also reject the *"low volatility synchronization"* hypothesis. That is, for Argentina and Brazil, we find that Argentina when Brazil is in a stable, low volatility period, Argentina is also in the low volatility period. A natural interpretation is that no-news in Brazil, are good news in Argentina. Overall, taking into account the economic linkages of Latin American markets, these results point out to a non-linear interdependence of these stock markets.

In Table 7, we present the results where we take Hong Kong as the "originator country." Overall these results suggest low correlations. Notice, however, that the correlations between Hong Kong and the Latin American countries increase during the periods of high volatility in Hong Kong. But as argued in Edwards and Susmel (2000) low or zero correlations do not imply independence. After all, contagion is a non-linear event, difficult to be captured by a standard correlation coefficient. We find dependence between Hong Kong-Argentina, and Hong Kong-Mexico. We cannot reject the independence hypothesis between Hong Kong-Brazil, and Hong Kong and Chile. This result might reflect the existence of capital controls in those countries during our sample. For Hong Kong-Argentina, and Hong Kong-Mexico, we also reject both versions of the synchronization hypothesis. [8]

In Table 8, we relax the assumption that correlations change only when the "originator country" changes of volatility state. We estimate the four-state SWARCH model allowing for correlations to change across each state. Table 8 presents these correlations coefficients. The pattern of increased correlations during high volatility periods of an originator country, implied by typical contagion stories, is only observed when Mexico is the originator. When Brazil or Hong Kong are taken as originators countries, the pattern is not very clear. For example, the correlation coefficient between Argentina and Brazil is significantly (twice or more) higher when both countries are in the low volatility state. Hong Kong and Chile also have unusual correlation patterns. The correlation coefficients are the highest when Chile is in the high volatility state. These results point out the shortcomings of arbitrarily splitting the sample and then using the correlation coefficients in the arbitrarily partitioned data set as a measured of contagion.

[8] 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

V. Concluding Remarks

In this paper we use weekly stock return data for a group of Latin American an Asian 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 and tend to be associated with common international crisis. Then, we examined the joint behavior of Latin American and Hong Kong stock return. We find that Latin American markets have dependent volatility processes. When Hong Kong, taken as a representative Asian market, is included, Chile and Brazil show no volatility dependence with that Asian market. Overall, we observe strong dependence among regional lines, especially among the Mercosur countries. Thus, our results are more supportive of interdependence than contagion stories.

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TABLE 1: Univariate Statistics for Stock Returns (USD) in Latin American Interest Rates

Series	Argentina	Brazil	Chile	Mexico	Hong Kong
Mean	0.225	0.179	0.290	0.247	0.243
SD	7.741	8.279	4.137	4.893	3.895
Skewness	-0.417	-1.239	-0.152	-0.982	-1.030
Kurtosis	11.916	8.372	17.477	6.458	6.047
JB-Normality test	3127.3*	1670.8*	6696.7*	998.56*	894.43*
LB(6)	23.26*	3.24	3.98	12.45	5.88
LBS(6)	88.58*	79.08*	125.73*	55.53*	12.11

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

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

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

	Argentina	Brazil	Chile
a_o	0.282 (0.23)	0.245 (0.22)	0.178 (0.15)*
a_1	0.073 (0.05)	0.074 (0.05)	0.271 (0.06)*
α_0	3.899 (1.09)*	1.179 (0.72)	3.504 (1.77)*
α_1	0.310 (0.09)*	0.290 (0.05)*	0.460 (0.11)*
β_1	0.656 (0.07)*	0.762 (0.04)*	0.402 (0.17)*
Likelihood	-1710.49	-1781.57	-1413.22
LB(6)	2.91	3.79	3.19
LBS(6)	0.87	0.86	2.46
Hansen-Standardized LR test (simulated 1% critical value)	5.62 (3.11)	6.17 (2.98)	3.07 (2.88)

	Mexico	Hong Kong
a_o	0.700 (0.19)*	0.437 (0.65)*
a_1	0.074 (0.05)	-0.033 (0.05)
α_0	3.313 (1.22)*	0.705 (0.34)*
α_1	0.283 (0.08)*	0.157 (0.05)*
β_1	0.614 (0.10)*	0.816 (0.05)*
Likelihood	-1539.72	-1421.93
LB(6)	1.74	5.50
LBS(6)	7.27	11.32
Hansen-Standardized LR test (simulated 1% critical value)	3.65 (3.03)	4.18 (3.23)

TABLE 3. ESTIMATION OF AR(1)-SWARCH(2,1)

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

	Argentina	Brasil	Chile
a_o	0.274 (0.20)	0.421 (0.24)	0.191 (0.14)
a_1	0.044 (0.05)	0.057 (0.05)	0.205 (0.05)*
α_0	11.478 (1.31)*	12.581 (2.35)*	5.495 (0.83)*
α_1	0.266 (0.07)*	0.234 (0.07)*	0.185 (0.08)
γ_2	10.177 (1.63)+	7.530 (1.18)+	7.831 (2.34)+
Likelihood	-1673.5	-1757.2	-1374.6
Likelihood SWARCH(3,1)	-1665.6	-1739.8	-1362.8
LB(6)	6.48	10.90	9.48
LBS(6)	2.44	4.55	7.36
Likelihood SWARCH(2,1)-L	-1673.4	-1755.9	-1368.9
Likelihood SWARCH(2,2)	-1673.4	-1755.1	-1374.6

	Mexico	Hong Kong
a_o	0.474 (0.17)*	0.469 (0.14)*
a_1	0.096 (0.05)	-0.017(0.04)
α_0	11.179 (1.03)*	6.858 (2.54)*
α_1	...	...
γ_2	6.915 (1.24)+	5.179 (1.10)+
Likelihood	-1513.1	-1405.0
Likelihood SWARCH(3,1)	-1509.2	-1399.1
LB(6)	8.73	9.78
LBS(6)	0.65	1.19
Likelihood SWARCH(2,1)-L	-1512.4	-1404.0
Likelihood SWARCH(2,2)	-1513.1	-1404.2

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

	MEX CRISIS 12/22/94	ASIAN CRISIS 10/23/97	RUS CRISIS 9/03/98	BRAZ CRISIS 1/14/94
ARGENTINA	2/09/95 (7)	10/30/97 (2)	8/06/98 (9)	xxx
BRAZIL	2/16/95 (5)	10/30/97 (3)	8/06/98 (9)	1/14/99 (2)
CHILE	3/09/95 (2)	xxx	xxx	xxx
MEXICO	12/15/94 (17)	10/23/97 (4)	8/06/98 (12)	1/14/99 (3)
HONG KONG	xxx	10/23/97 (1)	xxx	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 Argentina	Receptor Brazil	Receptor Chile
$a_{M,o}$	0.569 (0.17)*	0.462 (0.17)*	0.491 (0.17)*
$a_{M,1}$	0.053 (0.06)	0.073 (0.13)	0.057 (0.04)
$\alpha_{M,0}$	9.956 (1.20)*	10.606 (1.05)*	11.202 (1.01)*
$\alpha_{M,1}$	0.152 (0.13)	0.071 (0.05)	.001 (0.13)
$\gamma_{M,2}$	6.182 (1.24)+	4.526 (0.71)+	6.850 (1.23)+
$a_{Rec,o}$	0.455 (0.19)*	0.326 (0.22)	0.194 (0.13)
$a_{Rec,1}$	0.010 (0.04)	0.049 (0.05)	0.214 (0.05)*
$\alpha_{Rec,0}$	10.302 (1.37)*	10.795 (0.15)*	5.175 (0.63)*
$\alpha_{Rec,1}$	0.256 (0.07)*	0.140 (0.06)*	0.223 (0.07)*
$\gamma_{Rec,2}$	9.193 (1.41)+	8.072 (1.20)+	6.031 (1.13)+
$\rho_{M\text{-}LV}$	0.305 (0.06)*	0.200 (0.06)*	0.210 (0.05)*
$\rho_{M\text{-}HV}$	0.878 (0.03)*++	0.803 (0.03)*++	0.644 (0.07)*++
Likelihood SWARCH	-3102.6	-3202.5	-2850.2
Likelihood constant correlation	-3120.7	-3221.2	-2859.2
Likelihood 4 correlation coeff.	-3091.0	-3193.4	-2845.5
Likelihood-independent state	-3119.5	-3201.1	-2850.5
LR-independent states (p-value)	(>0.001)	(0.001)	(0.040)
Likelihood-common state	-3148.9	-3242.2	-2871.0
LR-common states (p-value)	(>0.001)	(>0.001)	(>0.001)
Likelihood-HV synchronization	-3111.7	-3215.1	-2859.1
LR-HV synchronization (p-value)	(>0.001)	(>0.001)	(>0.001)
Likelihood-LV synchronization	-3156.4	-3233.5	-2861.7
LR-LV synchronization (p-value)	(>0.001)	(>0.001)	(>0.001)

Notes:
* significant at the 5% level
+ significantly different than 1 (null hypothesis under no-switching)
++ significantly different state-dependent correlation coefficients (null hypothesis both correlation coefficients are equal)

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

	Coefficients (Standard errors)	
	Receptor Argentina	Receptor Chile
$a_{M,o}$	0.394 (0.24)*	0.507 (0.25)*
$a_{M,1}$	0.033 (0.05)	0.026 (0.05)
$\alpha_{M,0}$	15.054 (1.90)*	16.352 (2.66)*
$\alpha_{M,1}$	0.289 (0.08)*	0.224 (0.08)*
$\gamma_{M,2}$	5.960 (0.89)+	8.073 (1.36)+
$a_{Rec,o}$	0.320 (0.20)	0.173 (0.13)
$a_{Rec,1}$	0.022 (0.04)	0.199 (0.04)*
$\alpha_{Rec,0}$	11.341 (1.33)*	5.046 (0.73)*
$\alpha_{Rec,1}$	0.221 (0.07)*	0.226 (0.09)*
$\gamma_{Rec,2}$	9.344 (1.48)+	7.107 (1.67)+
$\rho_{M\text{-}LV}$	0.561 (0.05)*	0.321 (0.06)*
$\rho_{M\text{-}HV}$	0.199 (0.06)*++	0.271 (0.08)*
Likelihood SWARCH	-3376.0	-3101.8
Likelihood constant correlation	-3382.3	-3101.9
Likelihood 4 correlation coeff.	-3375.4	-3097.9
Likelihood-independent state	-3394.8	3112.1
LR-independent states (p-value)	(>0.001)	(>0.001)
Likelihood-common state	-3394.5	3106.0
LR-common states (p-value)	(>0.001)	(0.009)
Likelihood-HV synchronization	-3394.2	-3109.2
LR-HV synchronization (p-value)	(>0.001)	(>0.001)
Likelihood-LV synchronization	-3381.4	-3105.6
LR-HV synchronization (p-value)	(0.062)	(0.027)

TABLE 7: HONG KONG ORIGINATOR: SWARCH(2,1) BIVARIATE SYSTEM

	Coefficients (Standard errors)			
	Receptor Argentina	Receptor Brazil	Receptor Chile	Receptor Mexico
$a_{HK,o}$	0.479 (0.14)*	0.500 (0.14)*	0.476 (0.14)*	0.511 (0.15)*
$a_{HK,1}$	-0.038 (0.04)	-0.032 (0.04)	-0.033 (0.04)	-0.025 (0.04)
$\alpha_{HK,0}$	6.854 (0.76)*	6.898 (0.61)*	6.969 (0.63)*	7.167 (1.45)*
$\alpha_{HK,1}$	0.001 (0.11)	...	....	0.002 (0.20)
$\gamma_{HK,2}$	5.319 (0.78)+	5.141 (0.74)+	5.312 (0.79)+	5.357 (0.87)*+
$a_{Rec,o}$	0.403 (0.14)*	0.492 (0.23)*	0.226 (0.14)	0.546 (0.17)*
$a_{Rec,1}$	0.025 (0.04)	0.053 (0.05)	0.185 (0.04)*	0.086 (0.04)
$\alpha_{Rec,0}$	10.164 (1.37)*	12.200 (2.20)*	7.332 (0.74)*	10.860 (1.09)*
$\alpha_{Rec,1}$	0.241 (0.07)*	0.232 (0.07)*	0.223 (0.08)*	0.046 (0.06)
$\gamma_{Rec,2}$	10.684 (1.41)+	8.169 (1.32)+	6.031 (2.07)+	8.217 (1.71)*
$\rho_{M\text{-}LV}$	0.123 (0.05)*	0.081 (0.06)	0.127 (0.02)*	0.236 (0.05)*
$\rho_{M\text{-}HV}$	0.349 (0.08)*++	0.340 (0.08)*++	0.234 (0.06)*	0.400 (0.08)*
Likelihood SWARCH	-3061.6	-3149.1	-2770.5	-2887.1
Likelihood const. correl	-3064.0	-3151.9	-2770.9	-2888.2
Likelihood 4 correl coeff.	-3056.8	-3146.6	-2769.3	-2882.1
Likelihood- indep. state	-3064.7	-3152.4	-2773.4	-2891.7
LR-indep. states (p-value)	(0.045)	(0.159)	(0.056)	(0.032)
Likelihood-com. states	-3110.8			-2898.5
LR-com. states (p-value)	(>.001)			(.011)
Likelihood-HV synchr.	-3075.9			-2894.5
LR-HV synchr. (p-value)	(>.001)			(>.001)
Likelihood-LV synchr.	-3091.1			-2893.0
LR-LV synchr. (p-value)	(>.001)			(.001)

TABLE 8: SWARCH(2,1,2) STATE DEPENDENT CORRELATIONS

	LV_{OR} - LV_{REP}	LV_{OR} - HV_{REP}	HV_{OR} - LV_{REP}	HV_{OR} - HV_{REP}
Originator : Mexico				
Argentina	0.506 (0.06)	0.055 (0.08)	0.649 (0.13)	0.891 (0.03)
Brazil	0.503 (0.06)	0.089 (0.07)	0.859 (0.04)	0.715 (0.07)
Chile	0.225 (0.06)	0.161 (0.13)	0.424 (0.12)	0.776 (0.05)
Originator: Brazil				
Argentina	0.574 (0.05)	>0.001 (0.01)	0.197 (0.13)	0.254 (0.08)
Chile	0.290 (0.06)	0.949 (0.04)	0.013 (0.11)	0.422 (0.10)
Originator: Hong Kong				
Argentina	0.159 (0.07)	0.062 (0.09)	0.539 (0.09)	0.036 (0.14)
Brazil	0.231 (0.10)	>0.001 (0.01)	0.523 (0.12)	0.226 (0.10)
Chile	0.072 (0.07)	0.375 (0.15)	0.201 (0.11)	0.333 (0.21)
Mexico	0.234 (0.06)	0.672 (0.15)	0.617 (0.10)	0.155 (0.11)

FIGURE 1. Argentina:SWARCH(2,1) Volatility States

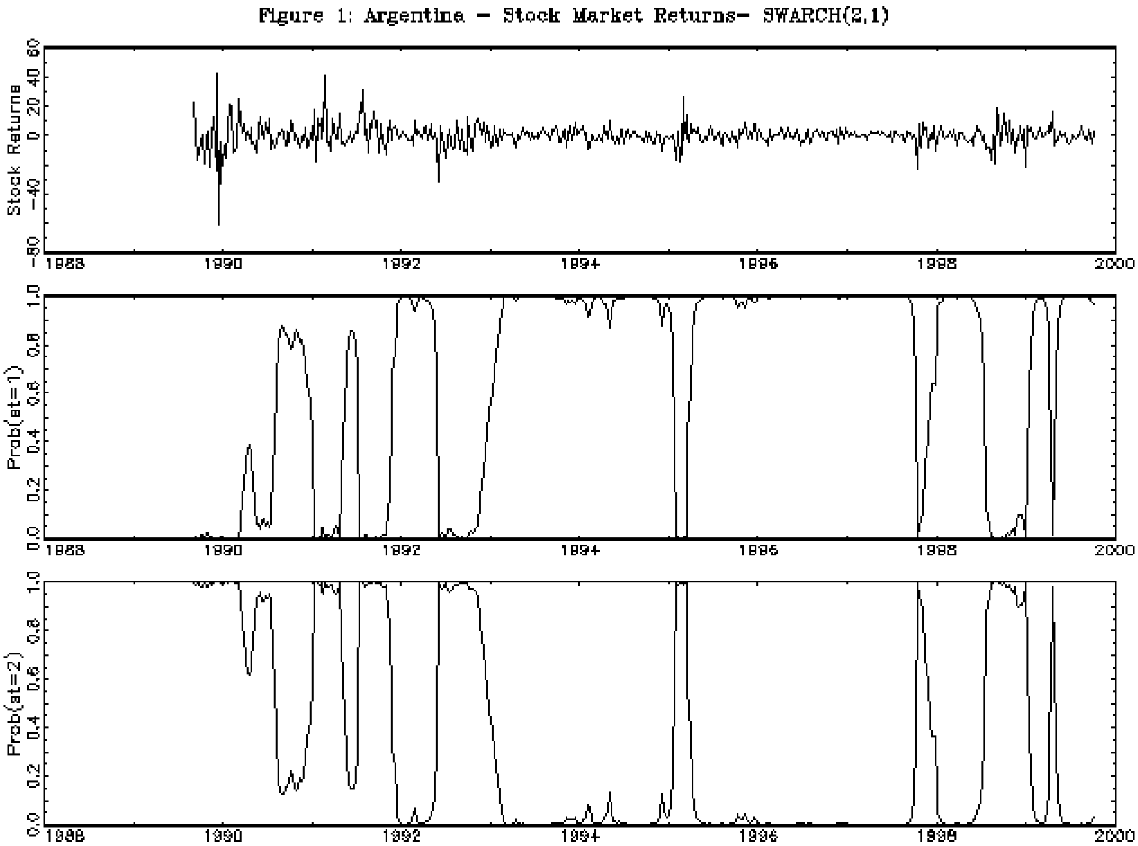

FIGURE 2. Brazil:SWARCH(2,1) Volatility States

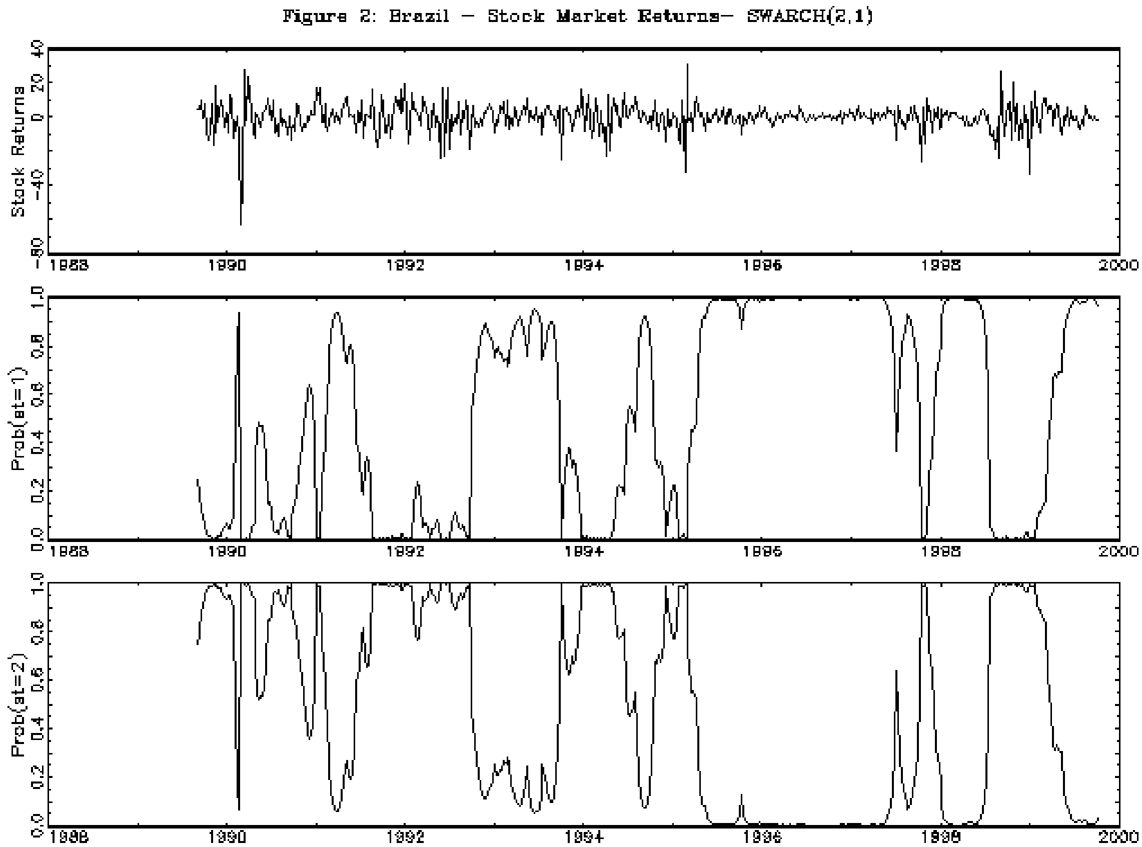

FIGURE 3. Chile:SWARCH(2,1) Volatility States

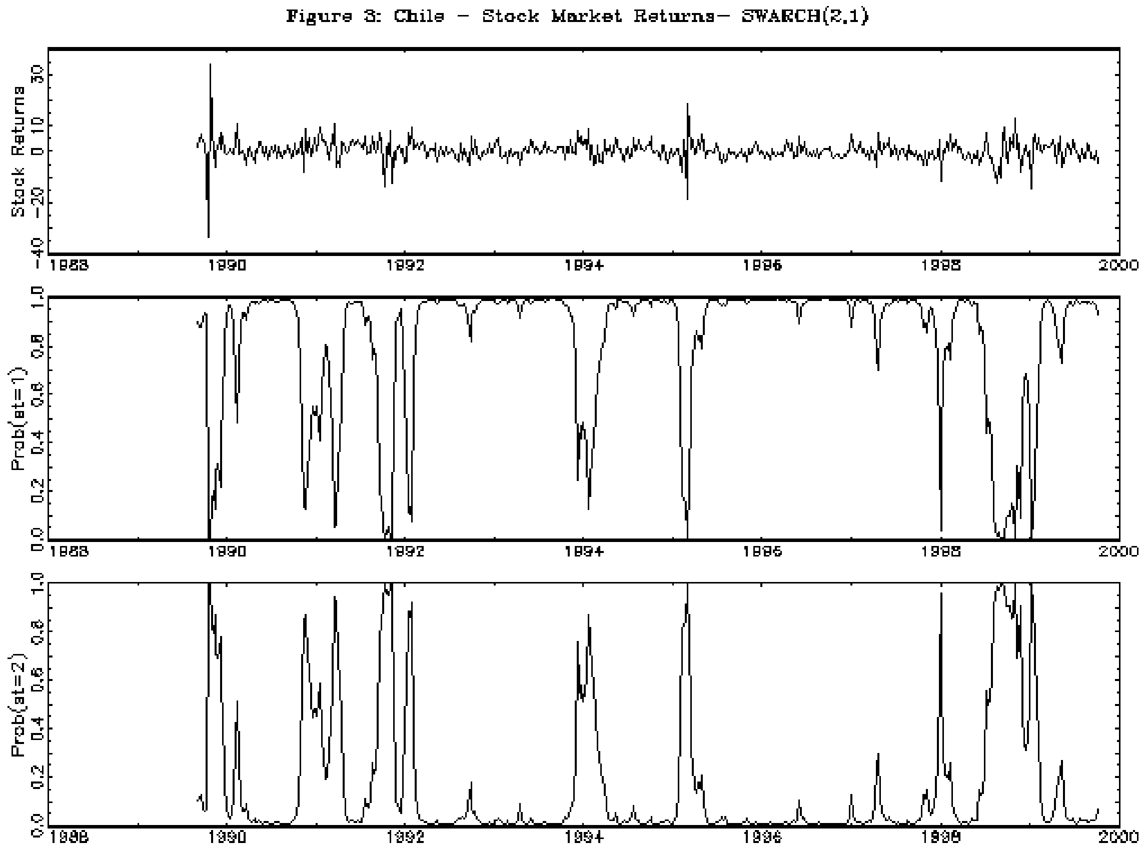

FIGURE 4. Mexico:SWARCH(2,1) Volatility States

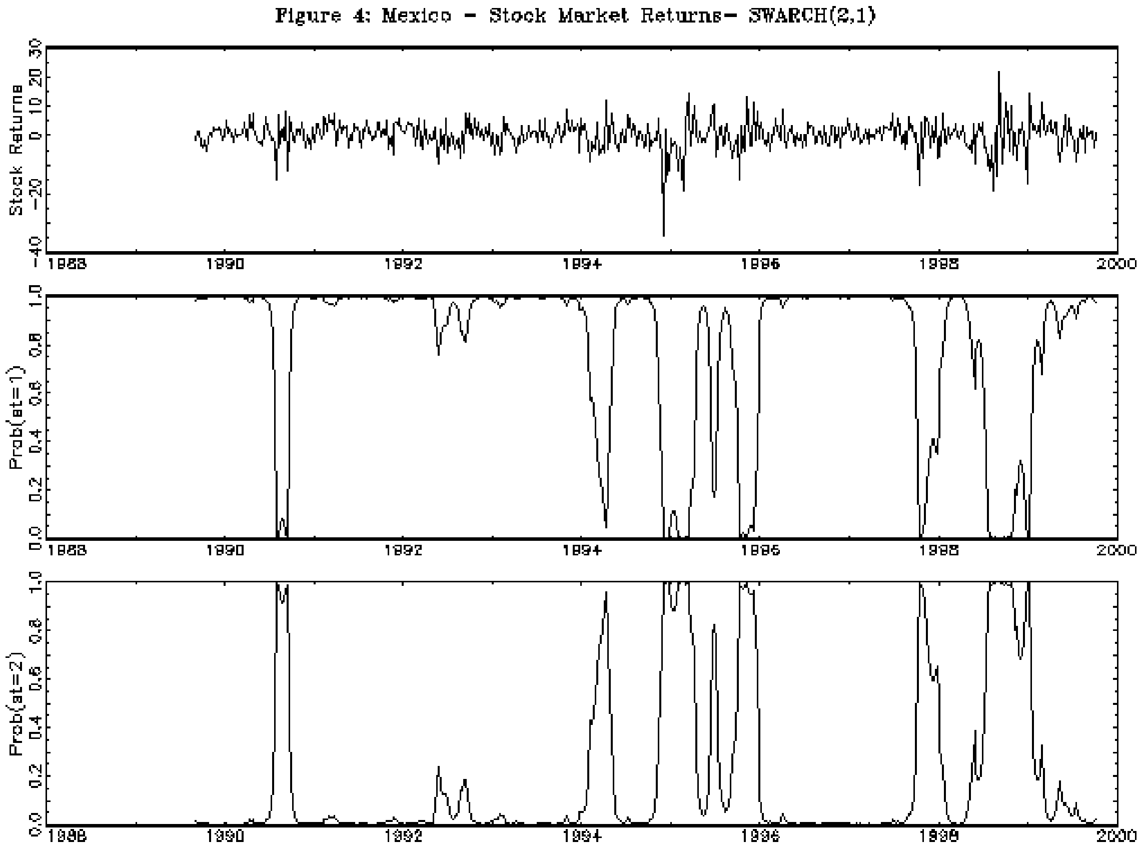

FIGURE 5. Hong Kong:SWARCH(2,1) Volatility States

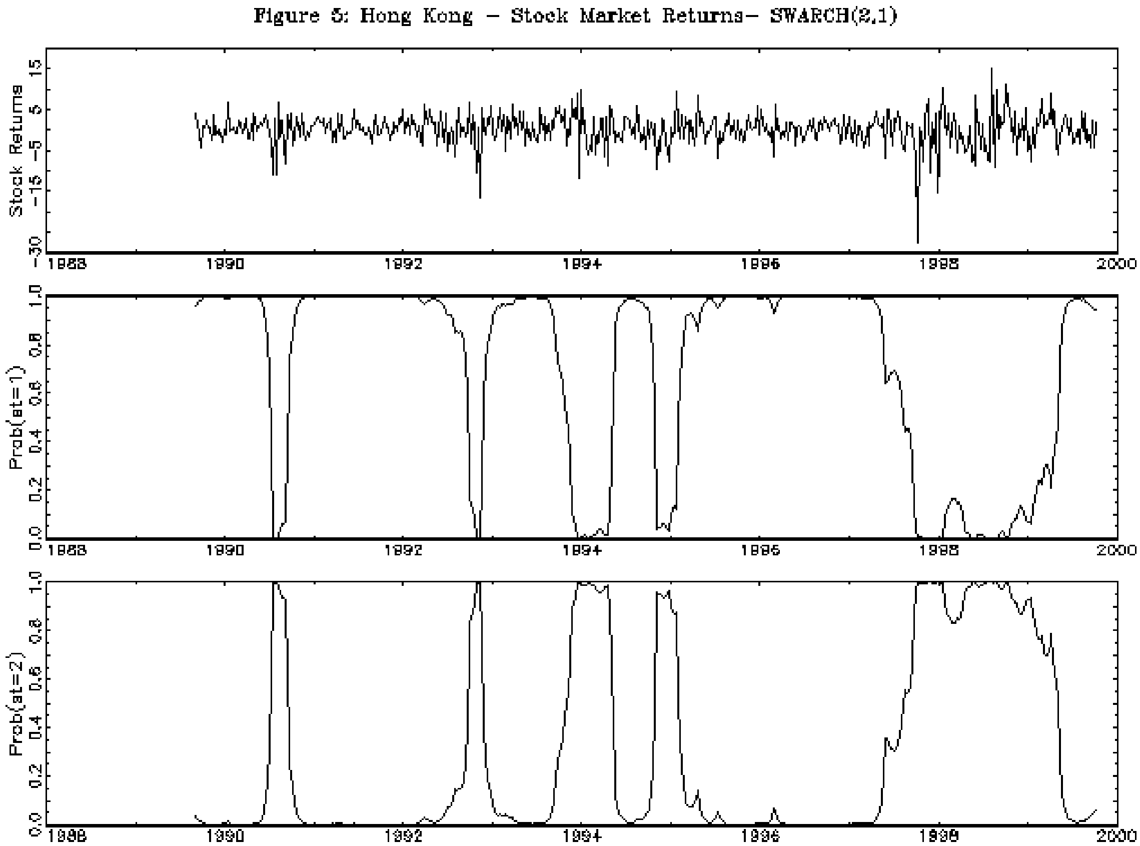

FIGURE 6. All Countries: SWARCH(3,1) Unusually High Volatility State

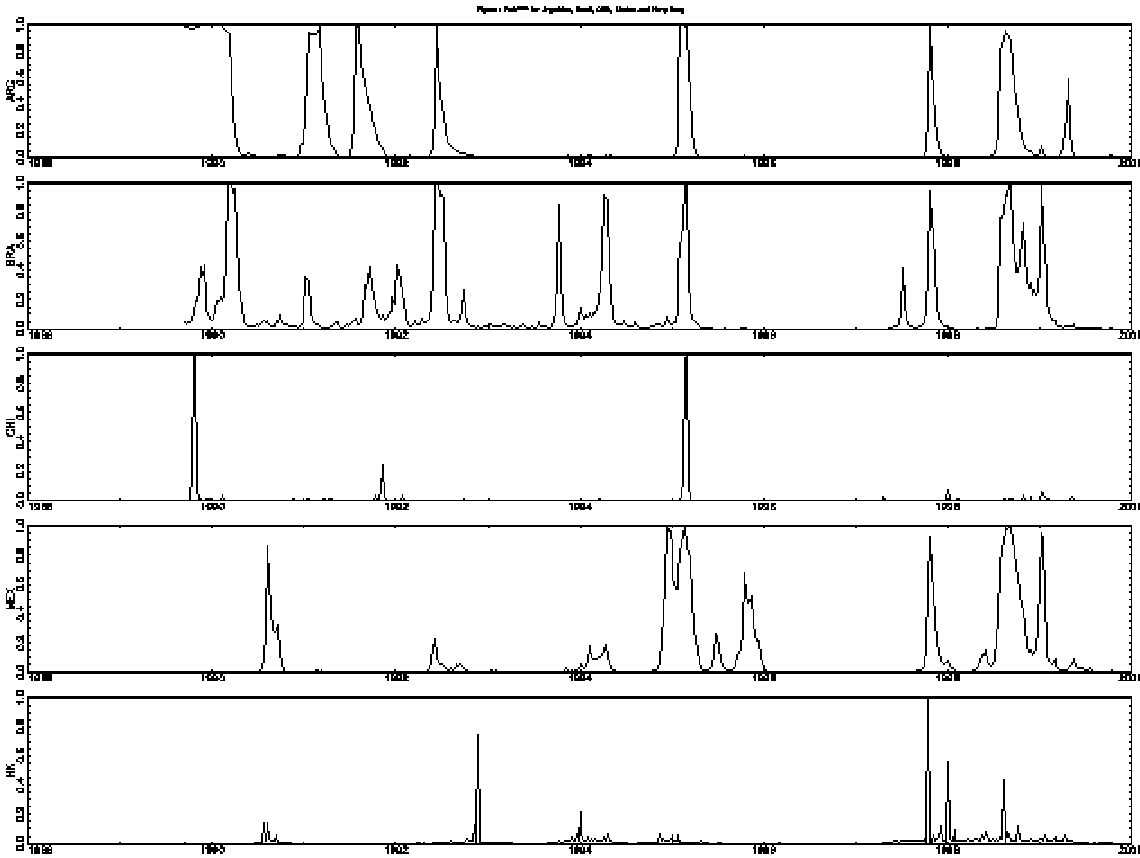

FIGURE 7. Mexico-Argentina: Bivariate SWARCH(2,1) Volatility States

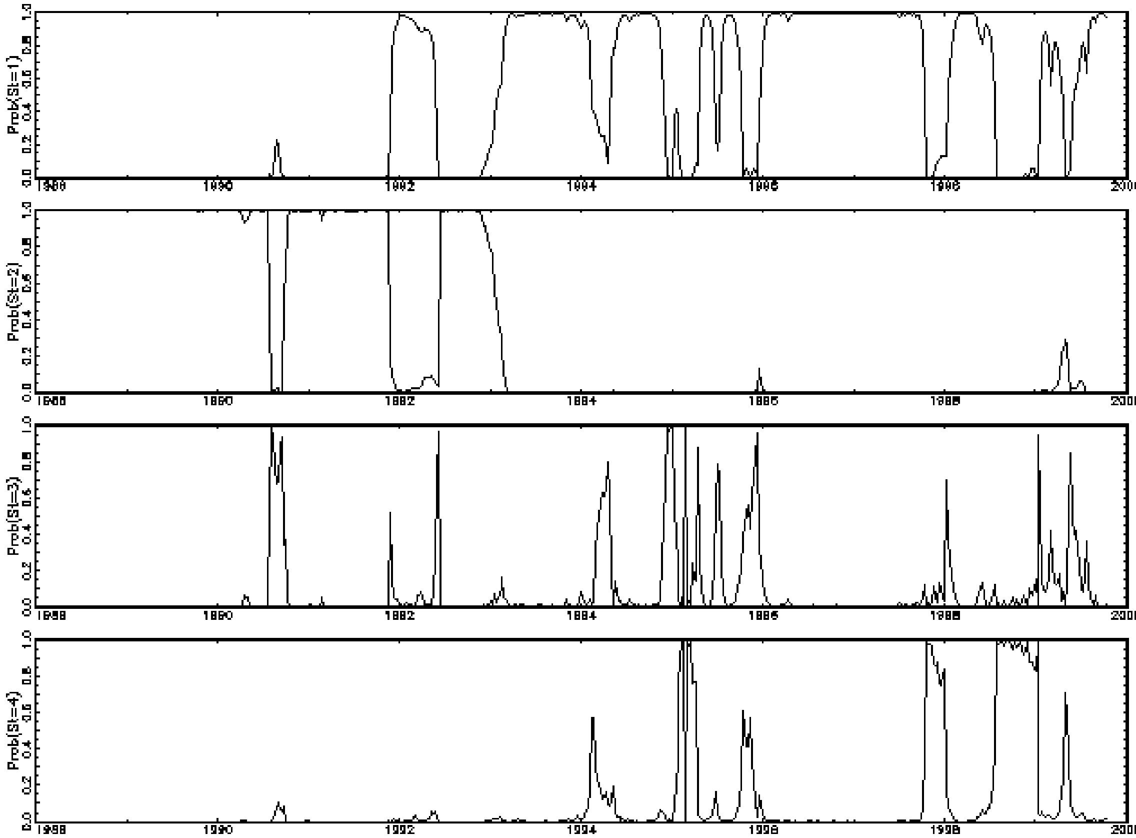

FIGURE 8. Mexico-Brazil: Bivariate SWARCH(2,1) Volatility States

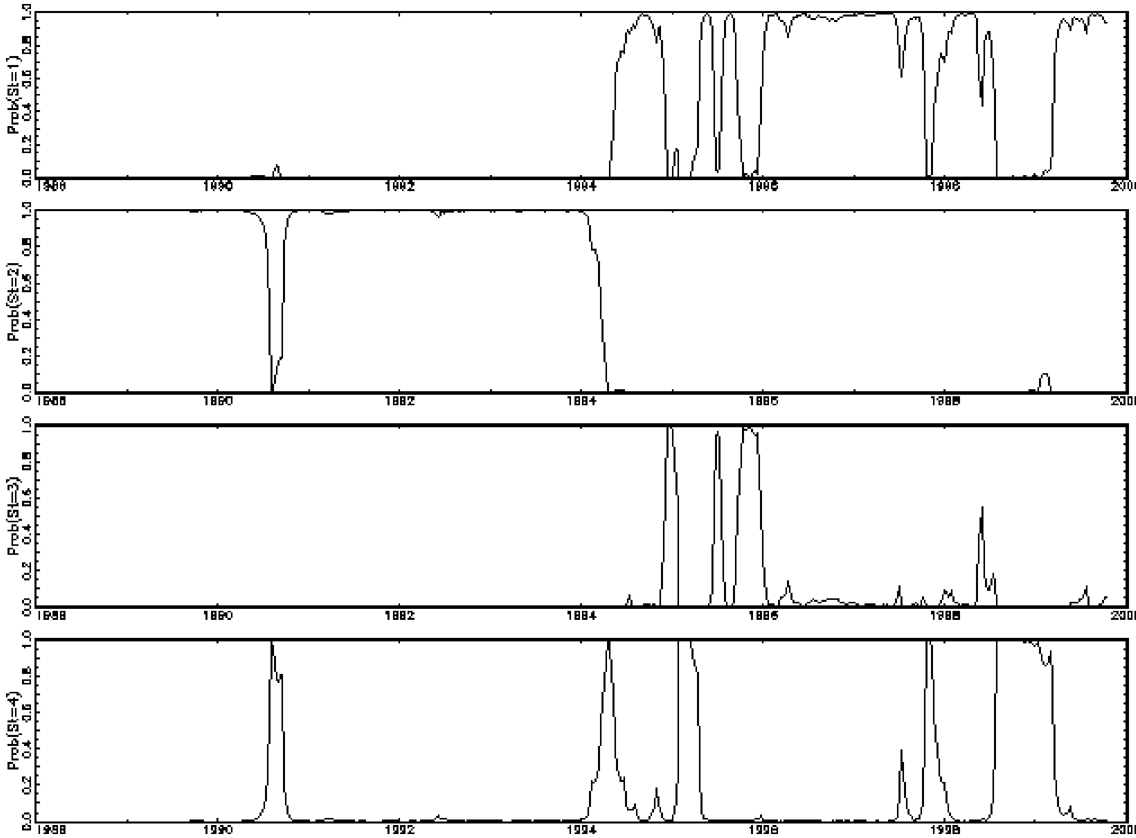

FIGURE 9. Mexico-Chile: Bivariate SWARCH(2,1) Volatility States

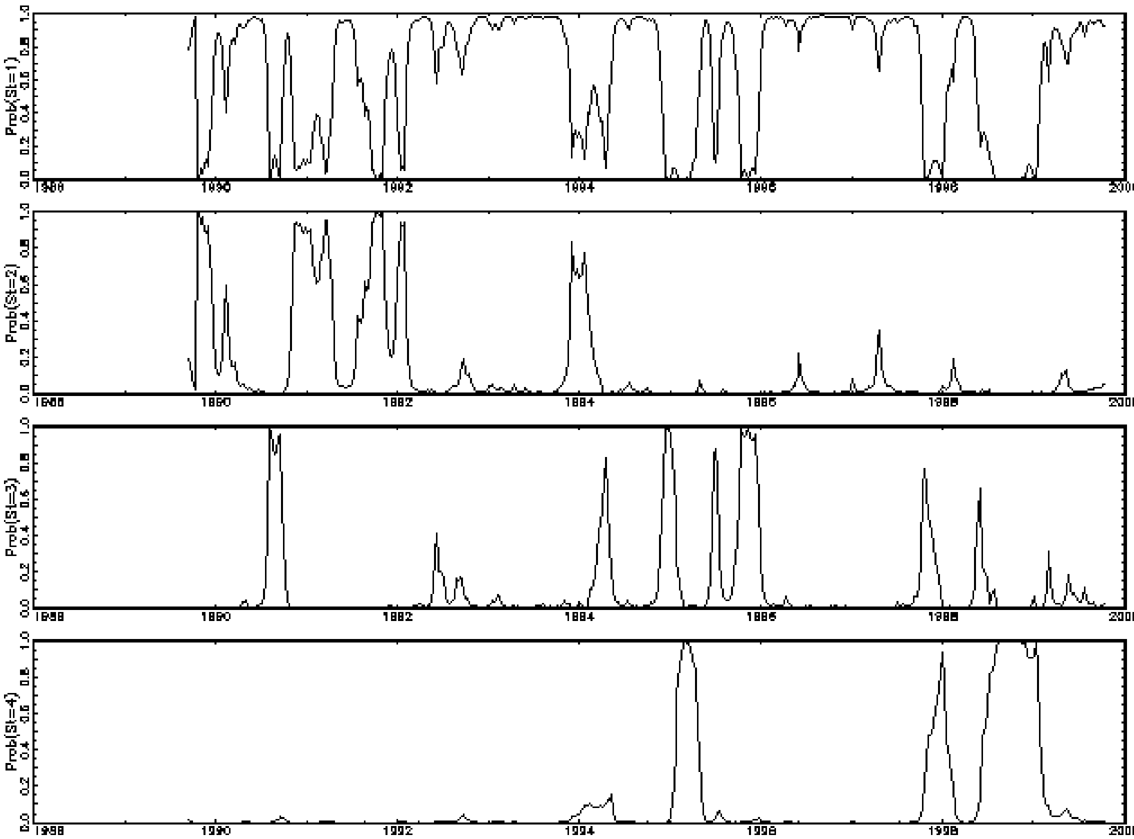

FIGURE 10. Brazil-Argentina: Bivariate SWARCH(2,1) Volatility States

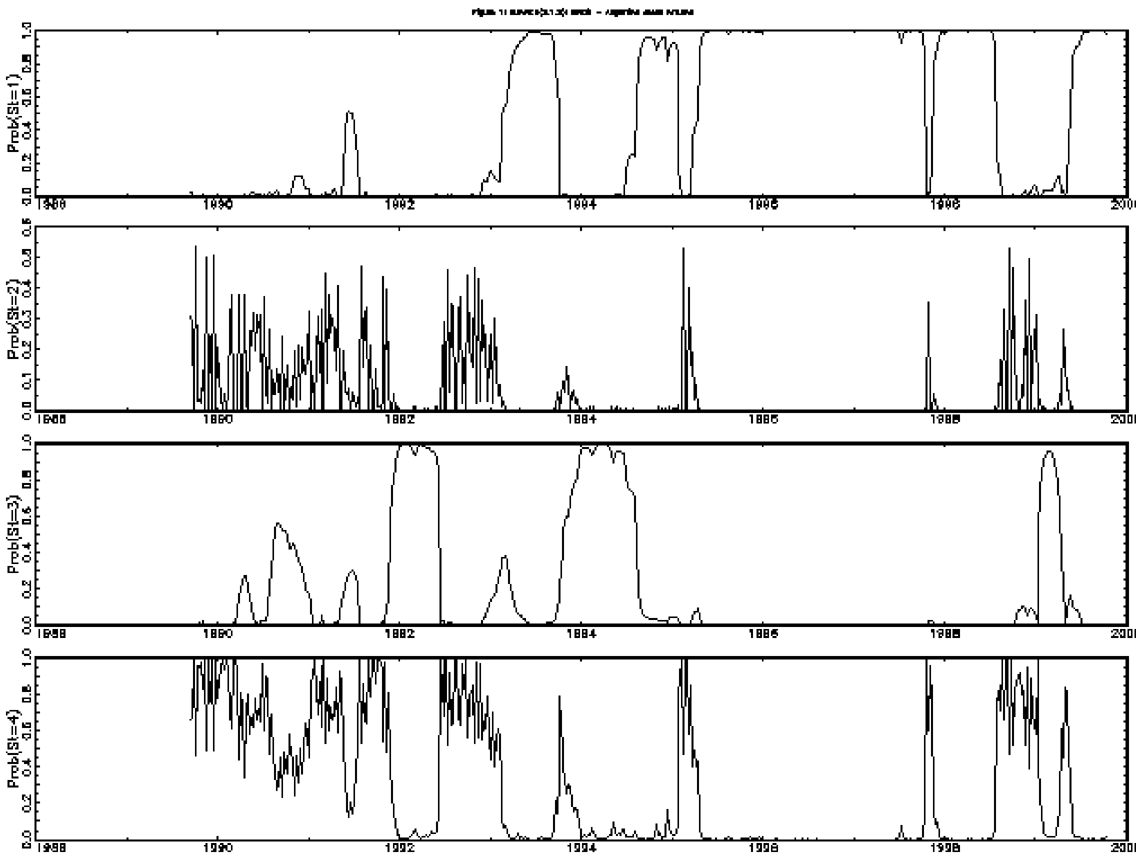

FIGURE 11. Brazil-Chile: Bivariate SWARCH(2,1) Volatility States

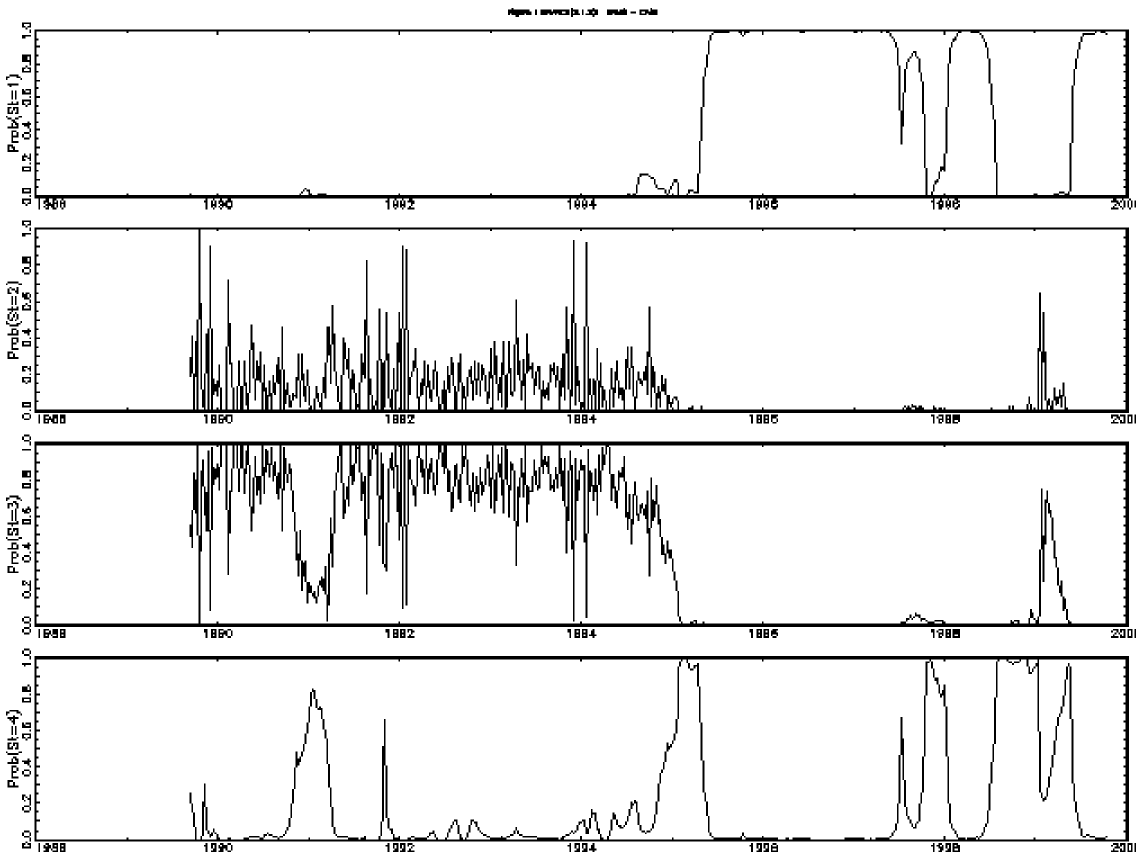

FIGURE 12. Hong Kong-Argentina: Bivariate SWARCH(2,1) Volatility States

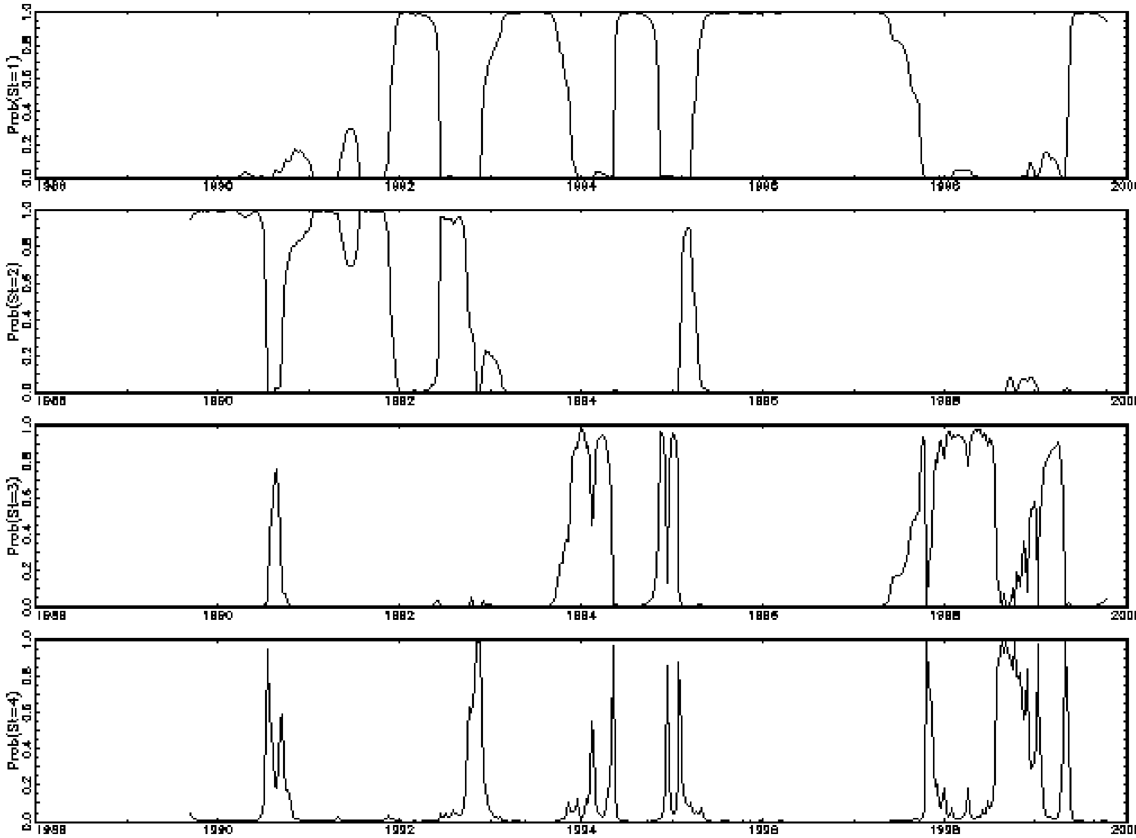

FIGURE 13. Hong Kong-Brazil: Bivariate SWARCH(2,1) Volatility States

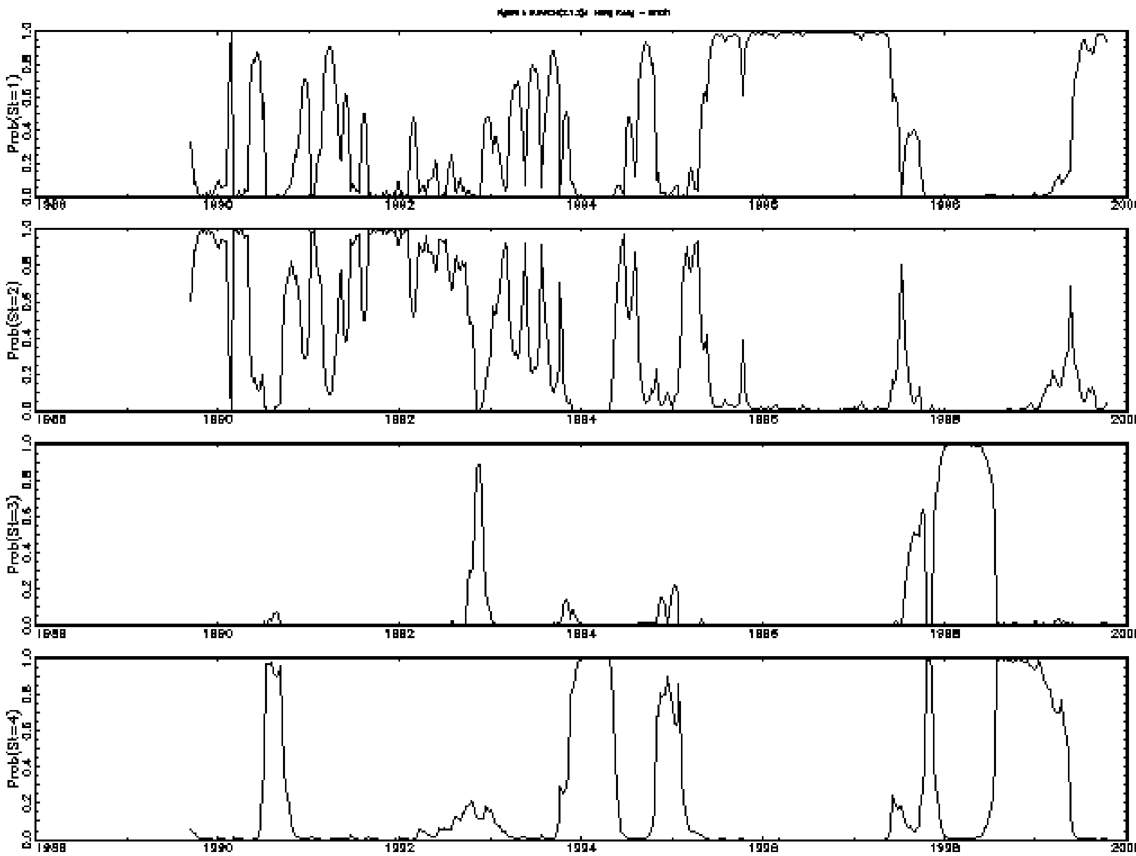

FIGURE 14. Hong Kong-Chile: Bivariate SWARCH(2,1) Volatility States

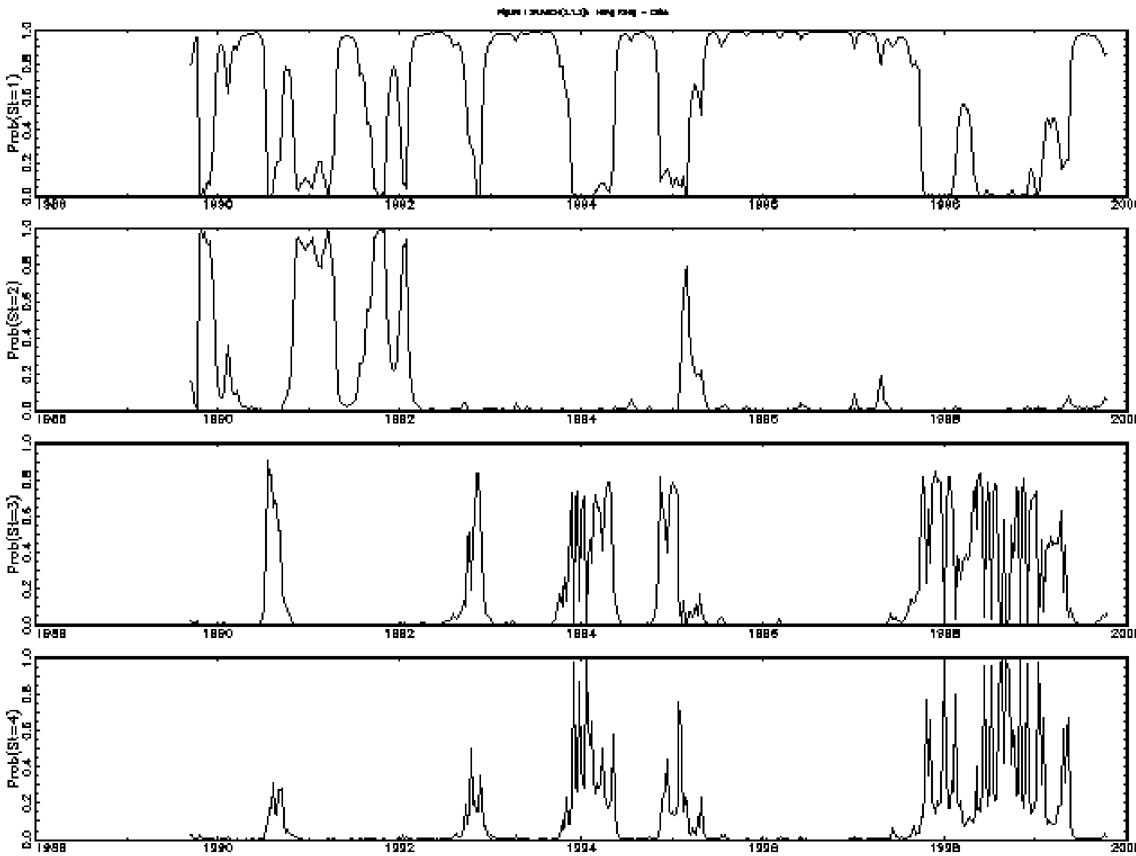

FIGURE 15. Hong Kong-Mexico: Bivariate SWARCH(2,1) Volatility States