

**UNIVERSIDAD DEL CEMA**  
**Av. Córdoba 374**  
**(1054) Capital Federal**

**Tel.: 4314-2269**  
**Fax: 4314-1654**

**CONTAGION AND VOLATILITY IN THE 1990s**

**Sebastian Edwards and Raul Susmel**  
**Julio 1999**  
**Nro. 153**

*Draft for Conference Presentation*

*May 28, 1999*

*Revision 1: June 12, 1999*

*Revision 2: June 16, 1999*

## **CONTAGION AND VOLATILITY IN THE 1990s**

by

**Sebastian Edwards**

**UCLA**

**Anderson Graduate School of Business**

**Los Angeles, CA 90095**

**And**

**National Bureau of Economic Research**

**Cambridge, MA 02138**

**e-mail: [sedwards@agsm.ucla.edu](mailto:sedwards@agsm.ucla.edu)**

**and**

**Raul Susmel**

**University of Houston**

**Department of Finance**

**College of Business Administration**

**Houston, TX 77204-6282**

**e-mail: [rsusmel@uh.edu](mailto:rsusmel@uh.edu)**

### **ABSTRACT**

In this paper we use weekly interest rate data for a group of Latin American countries to analyze the extent to which these countries have been subject to “contagion.” We are particularly interested in understanding volatility contagion, or the way in which periods of high volatility spillover across countries. Our paper departs from the existing literature in one important aspect: we allow the data to endogenously determine whether there have been periods of contagion. Then, we use the dates to study contagion periods. We find that contagion events are short-lived, lasting from two to seven weeks. We also find that the Asian and Russian crisis have had a greater effect on the Latin American countries than the pure Mexican and Brazilian crisis.

## **I. Introduction**

The currency crises of the 1990 have generated a renewed interest on issues of “contagion” in financial markets. Academics, private sector analysts and policy makers have raised a number of questions: Why is financial turmoil transmitted, so fast, from country to country? Why does instability affect countries that, apparently, have strong fundamentals? What can be done, if anything, to prevent contagion? Policy makers’ concerns are aptly captured by the following statement, by Mexico’s Finance Secretary Jose Angel Gurría, on the effects of the Russian collapse of August 1998 on Mexican financial markets:

“Ninety percent of Mexicans have never heard of the Duma, and yet the exchange rate and interest rates that they live with every day, were being driven by people with names like Kiriyenko and Chernomydrin and Primakov (1999, p 24).”

Theoretical efforts to understand contagion have been concentrated on two possible explanations of this phenomenon: (a) Panics that affect investors confidence, and that move the economy from a “good” to a “bad” equilibrium. And (b), weak fundamentals in the affected countries. Under this second explanation, an external shock can unleash a major collapse of the currency, and of the local banking sector (see Krugman 1999). At the empirical level, most studies on contagion have tried to identify whether the transmission of financial disturbances across countries, and especially across “distant” countries, has taken an “unusual” form. The standard approach is to concentrate on first moments of financial variables – stock market returns, rate of devaluation or interest rates --, and analyze whether, in the periods surrounding major crises, these variables experiment an unusual behavior. More specifically, when investigating the nature of contagion episodes, empirical studies tend to use one (or more) of the following approaches:

- investigate whether there are unusually large residuals in standard financial sector regression equations;
- investigate the existence of asymmetric responses to small and large shocks;
- try to identify the existence of breakpoints in econometric relationships.

In this paper we analyze financial contagion into three Latin American countries in the 1990s. Our analysis departs from the traditional literature in several ways: First, we look at both first and second moments of interest rate behavior; we are, in fact, particularly interested in understanding whether financial markets “volatility” is subject to contagion. Are periods of increased volatility in a particular country, transmitted to other nations? Second, we ask the data to “endogenously” tell us whether there has been contagion. That is, instead of imposing a date (or time interval) for the contagion effect to manifest itself, we look for “break points.” We do this by using a variant of the Hamilton and Susmel (1994) SWARCH approach.

Our analysis concentrates on three Latin American countries: Argentina, Chile and Mexico. These countries provide an interesting sample, since during most of the 1990s they were characterized by very different institutional arrangements, both in terms of exchange rate systems as well as rules governing capital mobility. While Argentina had a fixed exchange rate backed by a currency board, Mexico has had, since 1995, a floating exchange rate regime; Chile, on the other hand has had an exchange rate band system. Argentina and Mexico have had no capital controls during the period under study; between 1991 and 1998 Chile had controls on (short-term) capital inflows.

The paper is organized as follows: Section I is the introduction. In Section II we provide a brief review of the empirical literature on financial contagion, and we present the methodological approach followed in this paper. In Section III we discuss the data used in the analysis, and provide a brief description of recent currency crises and contagion episodes. In Section IV we present our econometric results. Finally, section V is the conclusions.

## **II. Contagion and Breakpoints in Financial Markets: Theory and Methodology**

Since the October 1987 global stock market crash, many studies have examined the interrelationships between asset prices across countries. Some of these papers present evidence suggesting that the correlation between equity markets was higher during the crash period, than either before or after the crash (e.g., Bennett and Kelleher (1988)). King and Wadhvani (1990) built a model where “large mistakes” could be transmitted across international markets. According to their setting, in international financial markets the

response to large shocks is different from the response to small shocks. Therefore, mistakes can be “contagious.”

Several papers have empirically looked at contagion of volatility (or “volatility spillovers”) across different equity markets. King and Engle, Ito and Lin (1990, 1992) document that “news” which is revealed when one foreign exchange market is open, affects return volatility in the market that opens next. These volatility spillovers are called “meteor showers” and appear to be present at various time periods for the yen-dollar exchange rate. Hamao, Ng and Masulis (1990) find volatility spillovers in international equity markets. More recently, Edwards (1998) finds volatility contagion in interest rates among Latin American emerging markets. None of these studies, however, found strong evidence that news in one market could predict the mean return in subsequent markets. Presumably such effects are arbitrated away by the market.

Longin and Solnik (1995) and Ramchand and Susmel (1998) find that when the U.S. equity market is highly volatile, world equity markets show a higher correlation with the U.S. equity market. In particular, Ramchand and Susmel (1998) using a regime-switching model are able to endogenously find different volatility regimes. They find that during high U.S. volatility regimes, the major equity markets are also more volatile.

Using a three-state specification to model the time-varying behavior of Latin American emerging equity markets, Susmel (1998) found that the high volatility state is composed of few and “unusual” observations. From the perspective of this paper this is a particularly interesting result, since we can, precisely, associate these unusual, high volatility observations with “contagion episodes.”

Interest rates are one of the many financial series that are, at least in principle, subject to change in regime. 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.

In this paper we define contagion as *a short-lived and unusual change in volatility induced by an exogenous shock*. In order to identify these changes in volatility, we use a switching specification based on the original work by Hamilton (1989). As pointed out

by Goodwin (1993), a particularly appealing feature of Hamilton's (1989) switching model is the ability to endogenously date the states of the economy. It is not the analyst that arbitrarily determines when a contagion period began; it is the data that tells if and when these contagion episodes have taken place.

Since we are primarily interested in volatility contagion, we use the model of Hamilton and Susmel (1994) to explicitly model the dynamics of switching variance. Although standard GARCH models are parsimonious, and are able to capture the time varying nature of volatility, they fails 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, recessions, among other. 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:

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

$$(2) \quad h_t / \gamma_{s_t} = \alpha_0 + \sum_{i=1}^q \alpha_i \varepsilon_{t-i}^2 / \gamma_{s_{t-i}} \quad i = 1, 2, \dots, q, \text{ and } s_t = 1, 2, \dots, K,$$

where the  $\gamma$ 's are scale parameters that capture the change in regime. One of the  $\gamma$ 's is unidentified and, hence,  $\gamma_1$  is set equal to 1. Following Hamilton (1989), maximum likelihood estimation is straightforward.

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:

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

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 ( $s_{t-1}=2$ ), 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,"  $p(s_t, s_{t-1} | r_t, r_{t-1}, \dots, r_3)$ , 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,”  $p(s_t|r_T, r_{T-1}, \dots, r_{t-3})$ , 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, the smooth probabilities at time  $t$  are represented by a  $2 \times 1$  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.

We check our primary specification, which allows for regime changes only in the conditional variance, against several alternatives. We fit models with changes in regime in mean only, and with simultaneous changes in regime in mean and variance.

### III. The Data

Our analysis deals with weekly interest rate behavior in Argentina, Chile and Argentina during the 1990s. In order to provide some comparisons we also analyze data from Hong-Kong.

The data were taken from the *Datastream* data set. For the case of Argentina, which is the country we analyze in greater detail, we consider peso denominated 30 day deposit rates (ARS), as well as dollar denominated 30 day deposit rates (USD). Unfortunately, the sample size is not uniform across series. 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 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 basic data, for the four countries in our sample. The case of Argentina is particularly interesting. First, as may be seen, throughout most of the period the differential between peso and US Dollar rates declined, indicating that the currency risk was becoming smaller and smaller. Interesting enough, however, this

differential remained quite large; although the perceived probability of devaluation declined, it did not disappear. Second, both 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 are 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.

Mexican interest rates also present an interesting case. Naturally, domestic interest rates increased in the aftermath of the Mexican peso crisis of December of 1994. However, as the figure shows, Mexican interest rates also responded to major international crises. In fact, consistent with the quote from Secretary Gurria presented in the Introduction to this paper, 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, and major responses following the East Asian and Russian crises. In Section IV we provide the results from our econometric results, where we analyze volatility in an attempt to date interest rate contagion for these countries.

In Table 1 we present summary statistics for changes in Argentina's ARS deposit rate, the Argentinean USD deposit rate, the Argentinean spread (ARS-USD), the Chilean CLP CD rate, the Mexican MXM deposit rate, and the Hong Kong Dollar (HKD) interbank rate. Table 1 reports 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 interest rates have declining over time. For example, both, the ARS and the USD interest rates have been declining over the sample. with the ARS interest rate declining relatively more than the USD interest rate. The ARS interest rate is almost twice as volatile as the USD interest rate. The CLP interest rate has the highest volatility. The data shows the typical non-normality of financial time series. Normality is rejected by the



JB normality test. 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.

Table 2 estimates a simple AR(1)-GARCH(1,1) model. 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  $\alpha_1$  is unusual for high frequency financial time series. For the ARS-USD spread and the CLP rate,  $\beta_1$  is unusually low. Moreover, for three of the series, the sum of  $\alpha_1$  and  $\beta_1$  is a bit higher than one, which makes shocks to the conditional variance increasingly persistent over time.<sup>1</sup> 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.

Figures 2, 3, and 4 plot in the first panel the changes in interest rates and in the second panel the estimated GARCH(1,1) variance, for the ARS, the USD, and the ARS-USD spread, respectively. There is clear, visual evidence of periods where the variance is extraordinary high. Several of these high volatility periods coincide with the exogenous "contagion" shocks described above. Similar results hold for the CLP, MXM, and HKD interest rates.

A rigorous test of the null hypothesis of no regime-switching can be done 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.<sup>2</sup> We calculate Hansen's test for

<sup>1</sup> Again, it is usual to observe, in high frequency financial series, the so-called Integrated GARCH model, where  $\alpha_1 + \beta_1 = 1$ .

<sup>2</sup> To get around the problem of no identified parameters under the null, Hansen (1994) defines a function

$$q_i(\zeta) = L_i[\zeta, \lambda(\zeta)] - L_i[\zeta_0, \lambda(\zeta_0)],$$

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. With the exception of the CLP rate, the null hypothesis of no regime-switching can be rejected at the 1% level. The Hansen test for the CLP rate provides a standardized likelihood ratio test of 3.42, which is lower than the simulated 10% upper bound critical value of 3.55.

#### IV. Econometric Results

In this section, we use the Switching ARCH (SWARCH) model of Hamilton and Susmel (1994), described above, to identify periods of unusually high volatility or contagion. 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. For brevity, we will discuss the Argentinean series. Table 3 finds that the best model for Argentinean interest rates is a model with three states. We observe several regularities. First, for all series we notice that using the SWARCH( $K,q$ ) model causes the ARCH effects to be reduced. Second, the switching parameters, the  $\gamma_i$ 's, are significantly different than one in all three series. The interpretation of the  $\gamma_i$ 's is straightforward. For example, the ARS 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. Third, we find no evidence for an asymmetric effect of negative news on conditional volatility.

---

where  $L_t\{\zeta, \lambda(\zeta)\}$ , represents the conditional log likelihood of the  $t$ th observation when evaluated at  $\zeta$  and  $\lambda(\zeta)$ . The parameters  $\zeta$  and  $\lambda$  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  $\zeta$  under the alternative hypothesis, with  $Z$  consisting of these 345 possibilities considered. For any  $\zeta$ ,  $\lambda(\zeta)$  is estimated by maximizing the likelihood with respect to  $\lambda$ , given  $\zeta$ . Hansen (1994) proposes the following standardized test:

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

where  $\text{mq}$  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  $z$ .

The first panel of Figure 4 plots the weekly ARS interest rate changes, the other three panels plot the smoothed probabilities,  $\text{Prob}(s_t=i|y_T, y_{T-1}, \dots, y_3)$  for the change in natural gas prices. 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) system, that is, an observation belongs to state  $i$  if the smoothed probability  $\text{Prob}(s_t=i|r_T, r_{T-1}, \dots, r_3)$  is higher than .5. Changes in ARS interest rates switch between the moderate 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.

Ruge-Murcia (1995) discusses a different interpretation of the smoothed probabilities. They represent the best assessment of a rational agent of the credibility of the structural reform undertaken by the government. In this context, our results for Argentina suggest that economic agents started to assign a high credibility to Argentine policies only in late 1995, when the government had successfully withstood the speculative attack on the currency, that followed the Mexican collapse.

It should be pointed out, that the stays of the ARS interest rates in the high volatility state are correlated to foreign (exogenous) events. For example, the last, pure domestic, stay in the high volatility state is in 1994. All the post-1994 changes to the high volatility state coincide with the Mexican crisis, the Asian crisis, the Russian crisis, and the Brazilian crisis, respectively.

Similar to Figure 5, Figure 6 plots the weekly USD interest rate changes on the first panel and on the other three the smoothed probabilities. The USD results look different from the ARS results. Recall, however, that volatility for the USD interest rate is substantially lower than for the ARS interest rate. The volatility state with the longest duration is the low volatility state. But, there are ten changes of regimes between the low and moderate volatility states. Similar to the 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.

We are interested in checking if the regimes, for the ARS, USD and ARS-USD interest rates, 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 of each model. For the first model, we 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. As an example of the determination of states, in Figure 7, we report the states estimated using a mean-only-switching model for the ARS interest rate. When we allow for simultaneous mean and variance switching we find that the states are primarily driven by variance switching, not mean switching. In Figure 8, we report the states estimated using a simultaneous-mean-and-variance switching model for the ARS interest rate. The states are similar to the states that were determined by the SWARCH model. This result is confirmed by comparing Figure 4 and Figure 8.

We use this approach to identify periods of unusually high volatility in the other three countries in our sample: Brazil, Chile and Mexico. In every case, we fit a three-state SWARCH model for domestic interest rates -- see Section III for the description of the data. -- and as in the case of Argentina, we associate the "high" volatility state with contagion. Due to space considerations we don't report the actual SWARCH estimates; these are, however, available on request.

Table 4 contains a summary of our findings on the extent and duration of volatility contagion episodes for Argentina, Chile, Mexico and Hong-Kong. For each country, we ask three questions: (a) Can we identify "contagion" in the period surrounding the four major crises under study? (b) If present, when does the "contagion" episode begin? And (c) how long do these episodes last? Each entry, in Table 4, provides a starting date for the high volatility state and the number of weeks the economy was in the high volatility state in the period surrounding each crisis..

A number of interesting results emerge from this table. First, Argentina was subject to "volatility contagion" in all four crises. Interestingly enough, our SWARCH analysis dates the beginning of the Tequila contagion episode quite late -- March 10,

1995. This is to some extent surprising, and may be due to the fact that it was at that time when the credibility of the currency board became particularly low, and when instability intensified. One way to investigate whether this is a plausible interpretation is to consider a four-state model -- one where, in principle, we could distinguish contagion from "super contagion." Table 4 also shows that Argentina was subject to an Asia-related "contagion." The beginning date is October 31<sup>st</sup>, immediately after the Hong Kong Currency Board was subject of a speculative attack. As may be seen, volatility generated by the Russian and Brazilian crises also spilled over into Argentina. Our results suggest that in Argentina, all four "contagion" episodes were rather short lived, lasting no more than six weeks.

The results reported in Table 4 suggest that Chile was spared from a "Tequila"-induced contagion episode. However, Chile was not immune from "contagion" stemming from the other three crises. Notice, however, that in all three cases the identified beginning date of the "contagion" episode is later than in the either Argentina and Mexico. This suggests that Chile was only affected by financial turmoil once other countries in the region had succumbed to it. The fact that Chile was not spared from contagion after 1994, casts some doubts on the effectiveness of the country's controls on capital inflows as a device to protect the domestic financial sector from externally-induced volatility.

The results for Mexico suggest that it was affected by both the Asian and Russian crises. In contrast to Argentina and Chile, however, the degree of volatility of Mexico's financial sector was not affected by the Brazilian episode. This may be the result of two factors: first, the Brazilian crisis was largely anticipated, and Mexico's links (both real and financial) with Brazil are rather tenuous. Second, by early 1999 Mexico had recovered (most of) its credibility, and was able to deflect external turmoil.

Finally, the results for Hong Kong are quite interesting. First, they show that it was very briefly impacted by Mexico's "tequila" crisis in early 1995. Second, the high volatility state that begins with the Asian crisis (which, of course, in many ways is its own crisis), lasts for an extremely long period of time (52 weeks), and overlaps with the Russian episode. Third, and quite surprisingly, Hong Kong does not appear to have been affected by the Brazilian crisis of January 1999.

## **V. Concluding Remarks**

In this paper, we study the extent to which three Latin American countries have been subject to “contagion.” We define contagion as a short-lived and unusual change in volatility induced by an exogenous shock. In order to identify these changes in volatility and date contagion events we use a switching ARCH. We find that contagion events are short-lived, lasting from two to seven weeks. We also find that the Asian and Russian crisis have had a greater effect on the Latin American countries than the pure Mexican and Brazilian crisis.

## References

- Ball, C. and W. Torous (1995), "Regime Shifts in short term riskless interest rates" Working Paper, #15-95, unpublished manuscript, The Anderson School, UCLA.
- Bennet, P. and J. Kelleher (1988), 'The International Transmission of Stock Price Disruption in October 1987,' Federal Reserve Bank of New York Quarterly Review, Summer 1988, 13: 17-33.
- Edwards, S. (1998) "Interest rate Volatility, Contagion and Convergence: An Empirical Investigation of the Cases of Argentina, Chile and Mexico" Journal of Applied Economics, 1,1.
- Engle, R.F. (1982), "Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K.," Econometrica, 50, 987-1008.
- Engle, R.F. and V.K. Ng (1993), "Measuring and Testing the impact of news on Volatility," Journal of Finance, 48, 1749-1778.
- Engle, R. F., T. Ito, and W-L Lin (1990), 'Meteor Shower or Heat Waves. Heteroskedastic Intra-Daily Volatility in the Foreign Exchange-Market,' Econometrica, May 1990, 55: 525-542.
- Engle, R. F., T. Ito, and W-L Lin (1992), 'Where Does the Meteor Shower Come From? The Role of Stochastic
- Glosten, L.R., R. Jaganathan and D. Runkle (1993), "Relationship between the Expected Value and the Volatility of the Nominal Excess Return on Stocks," Journal of Finance, 48, 1779-1801.
- Goodwin, T.H. (1993), "Business-Cycle Analysis with a Markov-Switching Model," Journal of Business and Economic Statistics, 11, 331-339.
- Hamao, Y., R. Masulis, and V. Ng (1990), 'Correlations in Price Changes and Volatility across International Stock Markets,' Review of Financial Studies, 1990, 3: 281-308.
- Hamilton, James D. (1989), "A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle," Econometrica, 57, 357-384.
- Hamilton, James D. (1996), "Specification Testing in Markov-Switching Time Series Models," Journal of Econometrics, forthcoming.
- Hamilton, James D. and R. Susmel (1994), "Autoregressive Conditional Heteroskedasticity and Changes in Regime," Journal of Econometrics, 64, 307-333.
- Hamao, Y., R. Masulis, and V. Ng (1990), 'Correlations in Price Changes and Volatility across International Stock Markets,' Review of Financial Studies, 1990, 3: 281-308.

Hansen, B.E. (1992), "The Likelihood Ratio Test under Non-standard Conditions: Testing the Markov Trend Model of GNP," Journal of Applied Econometrics, 7, S61-S82.

Hansen, B.E. (1994), "Erratum: The Likelihood Ratio Test under Non-standard Conditions: Testing the Markov Trend Model of GNP," working paper, Boston College.

Kalimipalli, M. and R. Susmel (1999), "Switching Stochastic Volatility, Two-Factor Models and Term Structure," University of Houston, unpublished manuscript.

King, M. and S. Wadhvani (1990), 'Transmission of Volatility Between Stock Markets,' Review of Financial Studies, 1990, 3: 5-33.

Lamoreux, C.G. and W. D. Lastrapes (1990), "Persistence in Variance, Structural Change and the GARCH Model," Journal of Business and Economic Statistics, 5, 121-129.

Ljung, G. and G. Box (1978), 'On a Measure of Lack of Fit in Time Series Models,' Biometrika, March 1978, 65: 297-303.

Ruge-Murcia, F. (1995), "Credibility and Changes in Policy Regime," Journal of Political Economy, forthcoming.

Susmel, R. (1995), "Switching Volatility in International Equity Markets," Department of Finance, University of Houston, unpublished manuscript.



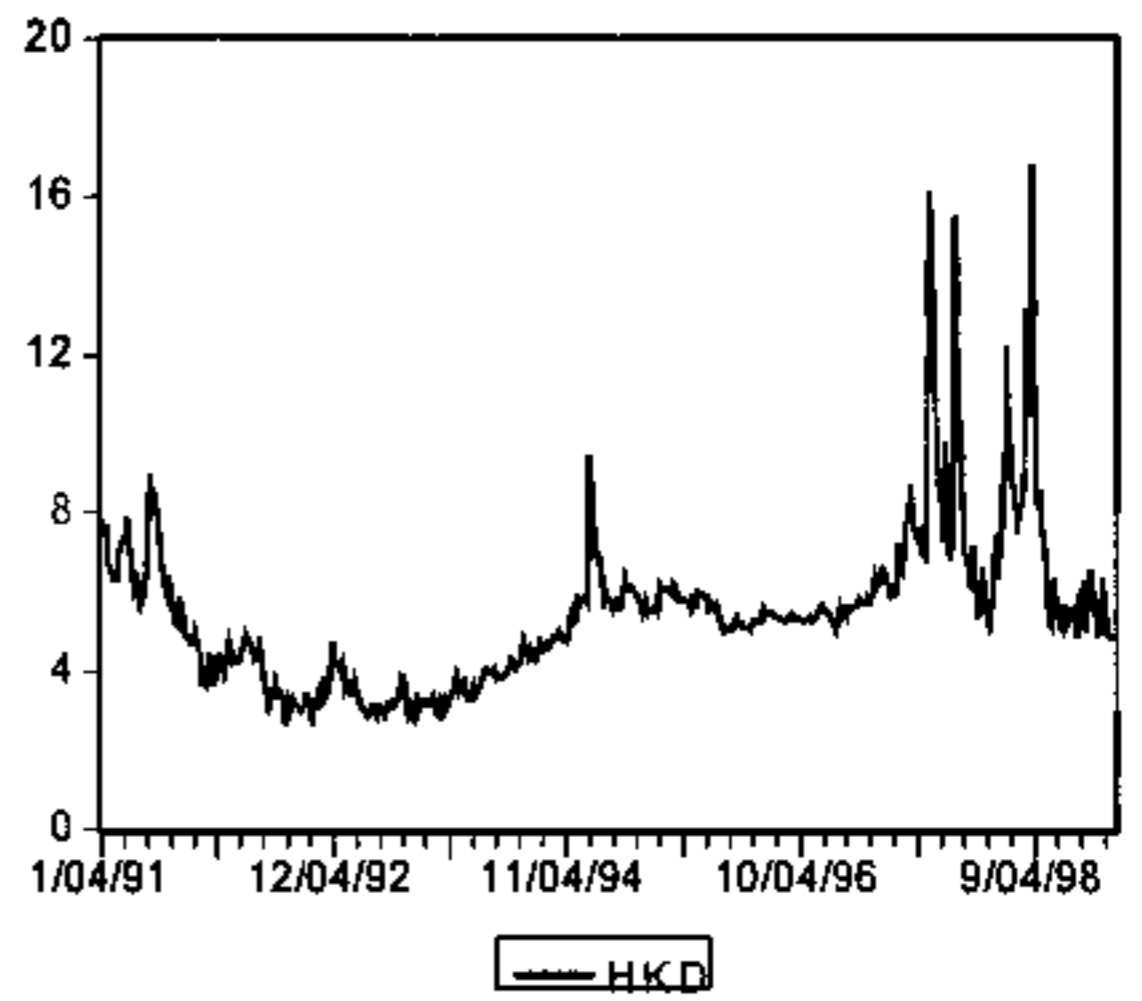
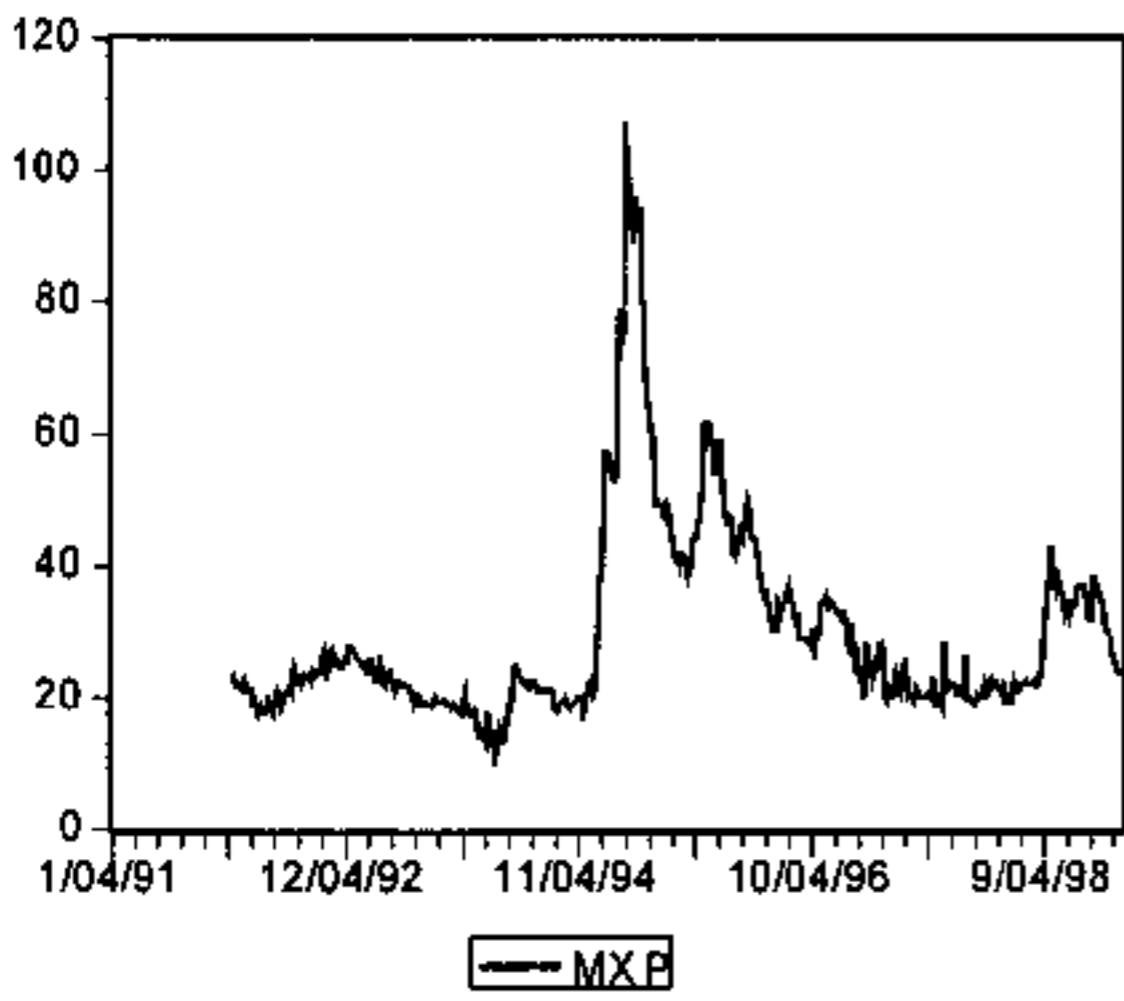
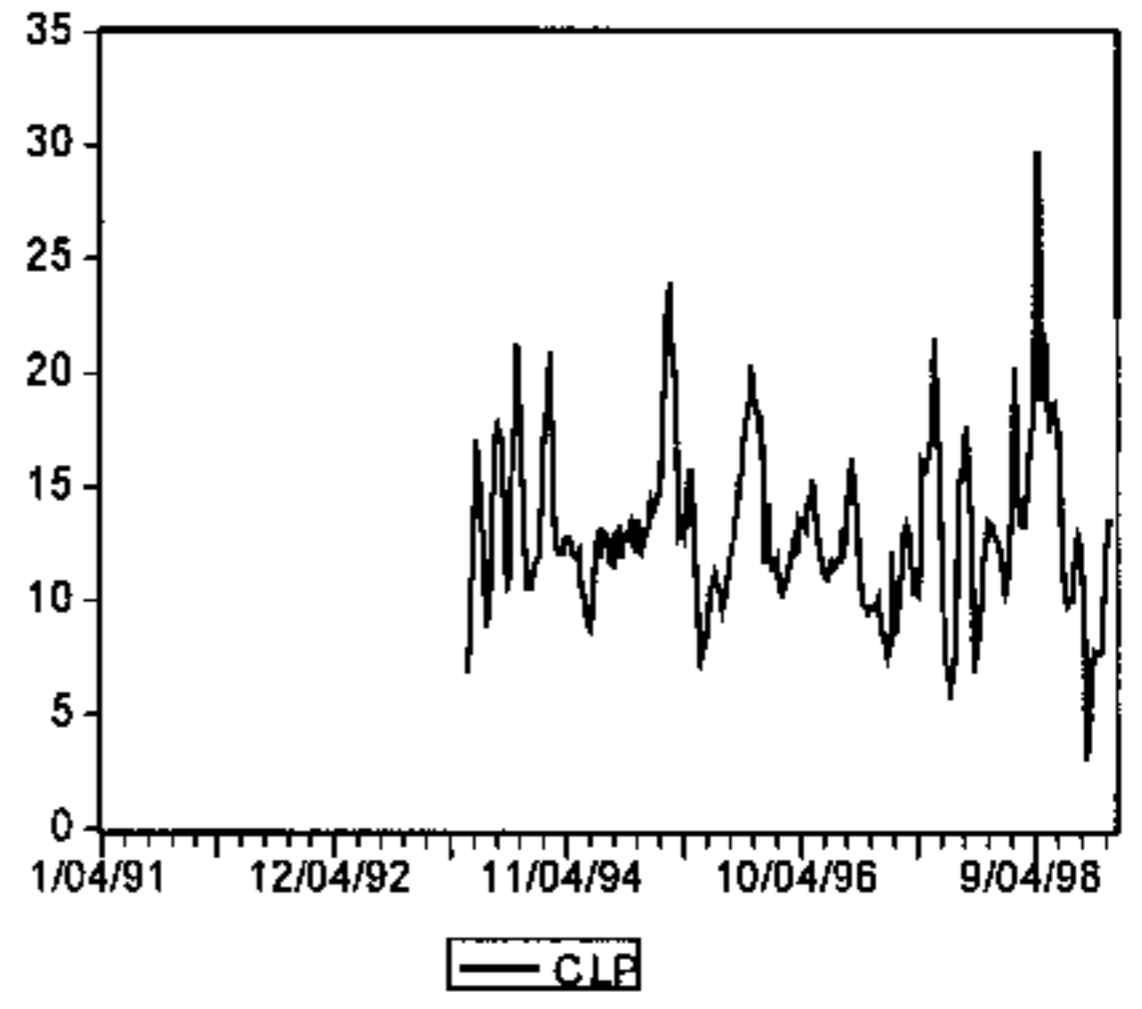
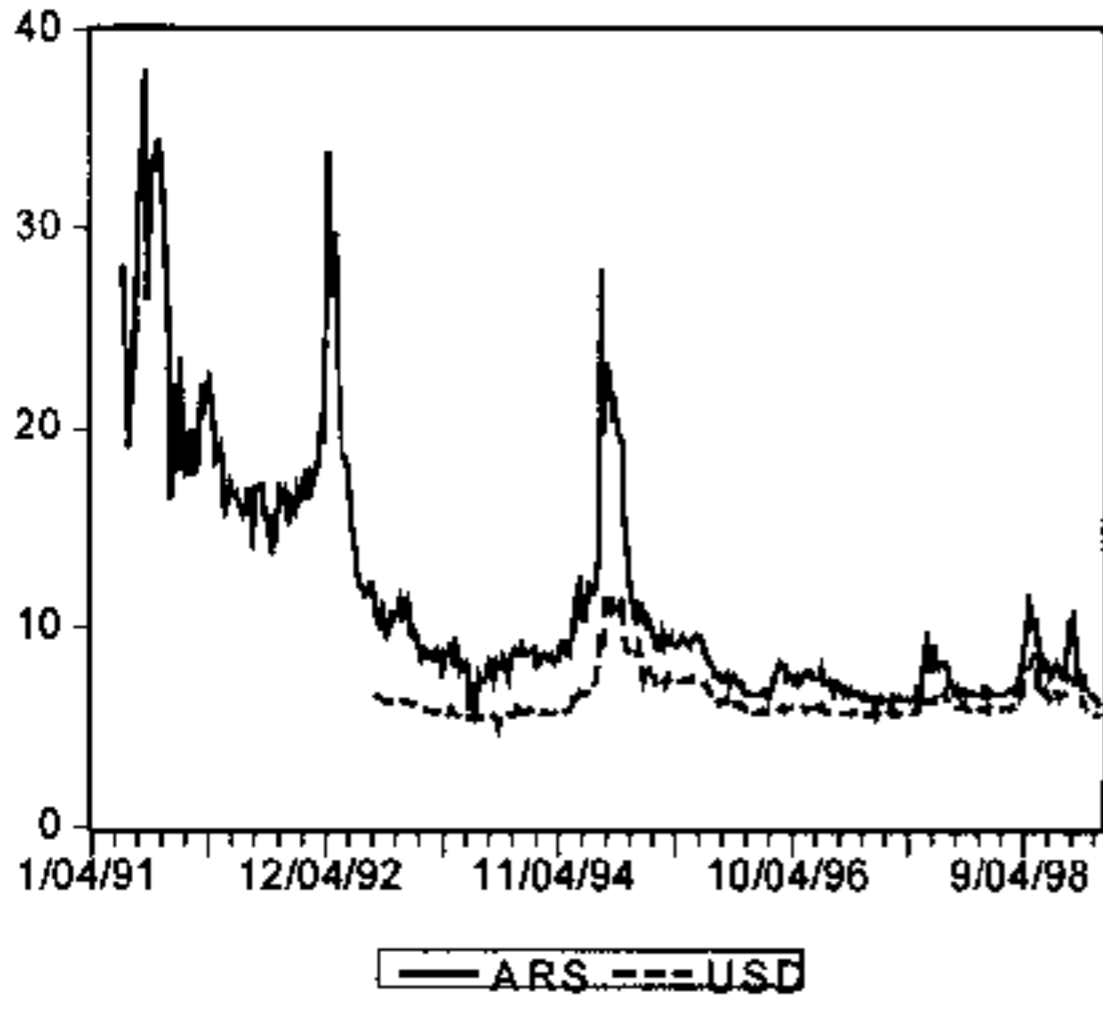


Figure 1: Interest Rates in Argentina, Chile, Mexico and Hong Kong: Weekly Data 1991-1999

TABLE 1: Univariate Statistics for Percentage Changes in Latin American Interest Rates

Series	90-day ARS	90-day USD	90-day ARS-USD	30-day CLP	28-day MXM	30-day HKD
Mean	-0.269	-0.040	-0.616	-0.081	-.022	-.078
SD	8.876	4.036	34.031	14.19	8.977	11.507
Skewness	0.922	0.445	-0.215	-1.470	1.088	1.767
Kurtosis	12.73	7.572	13.19	8.879	4.713	16.99
JB-Normality test	2865.81*	745.58*	2228.11*	987.82*	423.32*	5381.35*
LB(12)	35.40*	23.09*	53.34*	56.91*	12.33	39.36*
LBS(12)	36.65*	74.12*	63.69*	11.53	62.24*	105.04*
Number of Obs.	420	311	311	276	381*	433

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

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

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

	ARS	USD	ARS-USD
$a_0$	-0.745 (3.25)	-0.204 (1.48)	-1.838 (1.28)
$a_1$	-0.263 (4.53)	-0.256 (3.90)	-0.301 (4.50)
$\alpha_0$	2.563 (2.56)	1.247 (2.71)	0.003 (1.74)
$\alpha_1$	0.587 (5.47)	0.457 (3.51)	0.101 (1.80)
$\beta_1$	0.589 (11.30)	0.551 (5.5)	0.305 (1.55)
<b>Likelihood</b>	<b>-1405.3</b>	<b>-786.08</b>	<b>-1481.78</b>
<b>LB(12)</b>	<b>10.98</b>	<b>8.40</b>	<b>5.64</b>
<b>LBS(12)</b>	<b>7.17</b>	<b>3.76</b>	<b>1.14</b>
<b>Hansen-Standardized LR test (simulated 1% critical value)</b>	<b>5.43 (4.36)</b>	<b>6.40 (4.32)</b>	<b>4.37 (4.18)</b>

	CLP	MXM	HKD
$a_0$	-0.032 (0.05)	-0.244 (0.65)	0.077 (0.25)
$a_1$	0.379 (5.45)	-0.135 (2.16)	-0.234 (3.25)
$\alpha_0$	42.994 (3.02)	6.524 (3.65)	0.699 (0.90)
$\alpha_1$	0.638 (4.40)	0.169 (3.75)	0.233 (4.36)
$\beta_1$	0.294 (2.91)	0.763 (18.27)	.860 (47.52)
<b>Likelihood</b>	<b>-1055.3</b>	<b>-1329.3</b>	<b>-1551.02</b>
<b>LB(12)</b>	<b>36.94*</b>	<b>5.50</b>	<b>6.75</b>
<b>LBS(12)</b>	<b>4.44</b>	<b>10.75</b>	<b>1.07</b>
<b>Hansen-Standardized LR test (simulated 1% critical value)</b>	<b>3.42 (4.55)</b>	<b>7.49 (4.62)</b>	<b>5.82 (4.15)</b>

TABLE 3. ESTIMATION OF AR(1)-SWARCH(3,1): ARGENTINA ARS and USD Interest Rates

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

$$h_t / \gamma_{st} = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 / \gamma_{st-1}$$

	ARS	USD	ARS-USD
$a_0$	-0.487 (2.37)	-0.085 (0.80)	-1.439 (1.80)
$a_1$	-0.193 (3.53)	-0.271 (4.59)	-0.409 (8.91)
$\alpha_0$	6.804 (1.14)	1.633 (4.73)	25.568 (2.34)
$\alpha_1$	0.266 (3.05)	0.209 (1.96)	0.331 (3.51)
$\alpha_2$	....	0.064 (0.77)	0.247 (2.67)
$\gamma_2$	3.841 (4.54)	6.471 (2.74)	11.88 (2.62)
$\gamma_3$	35.31 (3.58)	35.39 (2.58)	161.90 (2.07)
Likelihood	-1352.4	-753.01	-1400.6
Likelihood SWARCH(3,q+1)	-1351.5	-753.00	-1399.5
LB(12)	13.57	11.02	5.02
LBS(12)	14.34	4.14	0.08
Likelihood SWARCH(2,1)	-1367.5	-759.09	-1412.4
Likelihood SWARCH(4,1)	-1358.9	-752.6	-1404.1
Likelihood SWARCH(K,q)-L-t	-1351.6	-753.6	-1399.8
Likelihood -mean only- K=3	-1435.29	-795.22	-1500.78
Likelihood -mean and var.- K=3	-1366.12	-752.32	-1407.82

**TABLE 4: IDENTIFYING CONTAGION EVENTS**

	<b>MEX CRISIS 12/30/94</b>	<b>ASIAN CRISIS 10/24/97</b>	<b>RUS CRISIS 9/04/98</b>	<b>BRAZ CRISIS 1/15/94</b>
<b>ARGENTINA</b>	3/10/95 (5)	10/31/97 (6)	8/28/98 (5)	1/15/99 (5)
<b>CHILE</b>	Xxx	12/29/95 (3)	9/18/98 (2)	1/29/99 (3)
<b>MEXICO</b>	Does not apply	10/24/97 (7)	9/04/98 (5)	xxx
<b>HONG KONG</b>	1/13/95 (2)	10/24/97 (52)		xxx

**Notes:**

Each entry provides a starting date for the high volatility state (3<sup>rd</sup> 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 3<sup>rd</sup> state during the given crisis.

FIGURE 2: ARG -INT RATES (ARS) - Time Varying GARCH(1,1) Variance

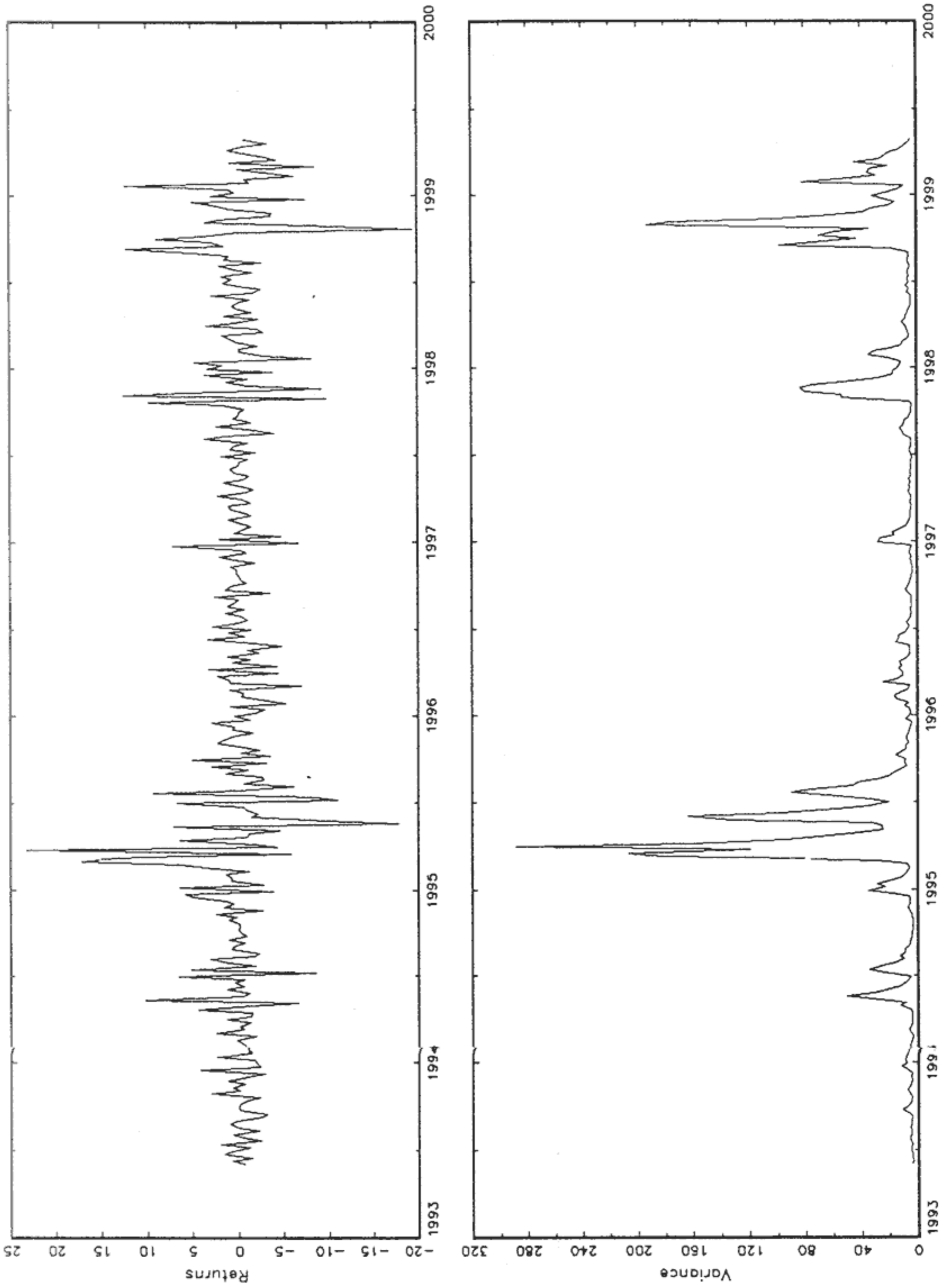


FIGURE 3: ARG -INT RATES (USD) - Time Varying GARCH(1,1) Variance

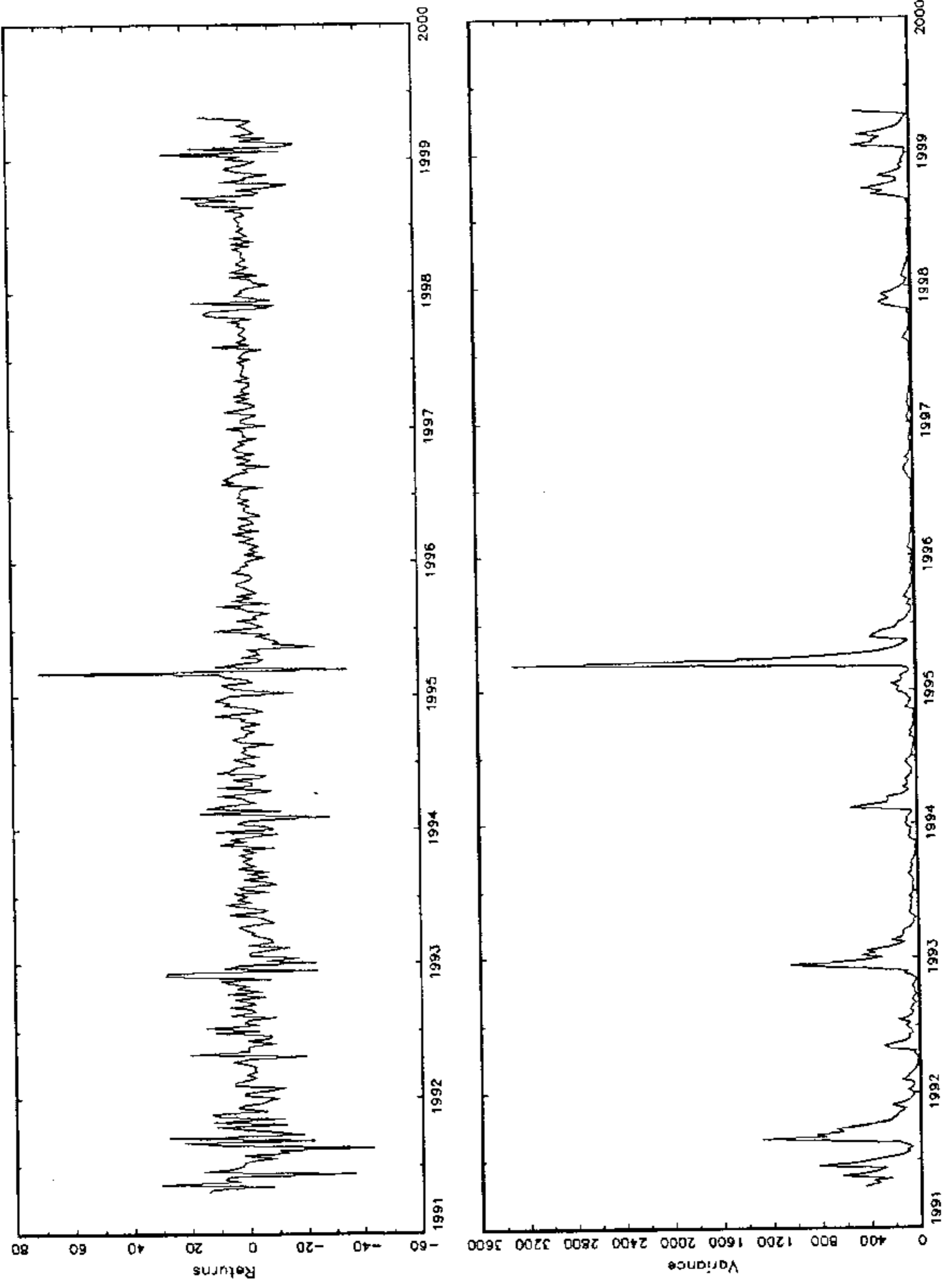


FIGURE 4: ARG -INT RATES (ARS-USD) - Time Varying GARCH(1,1) Variance

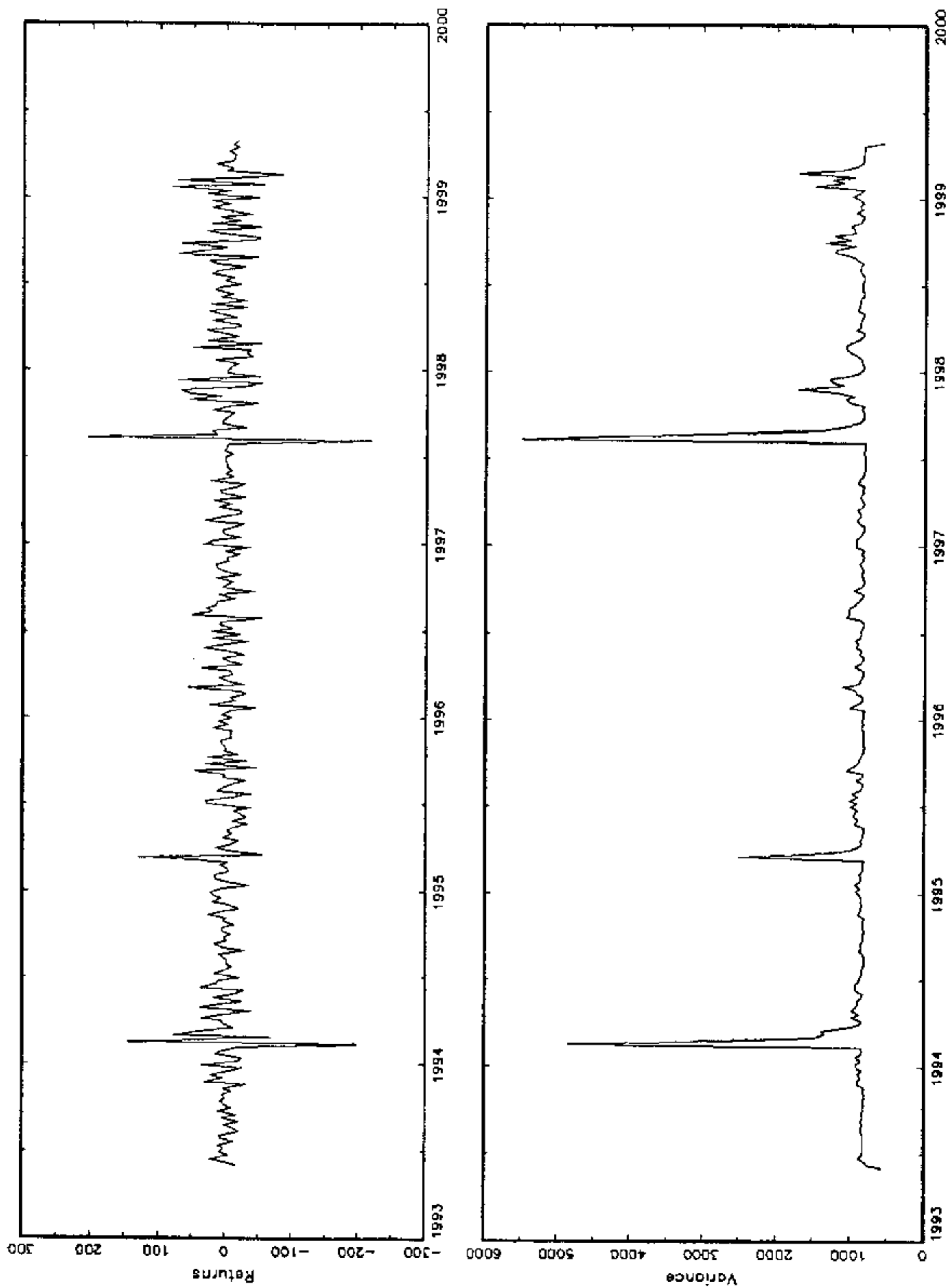




FIGURE 5: ARG -INT RATES (ARS) - SWARCH(3,1)

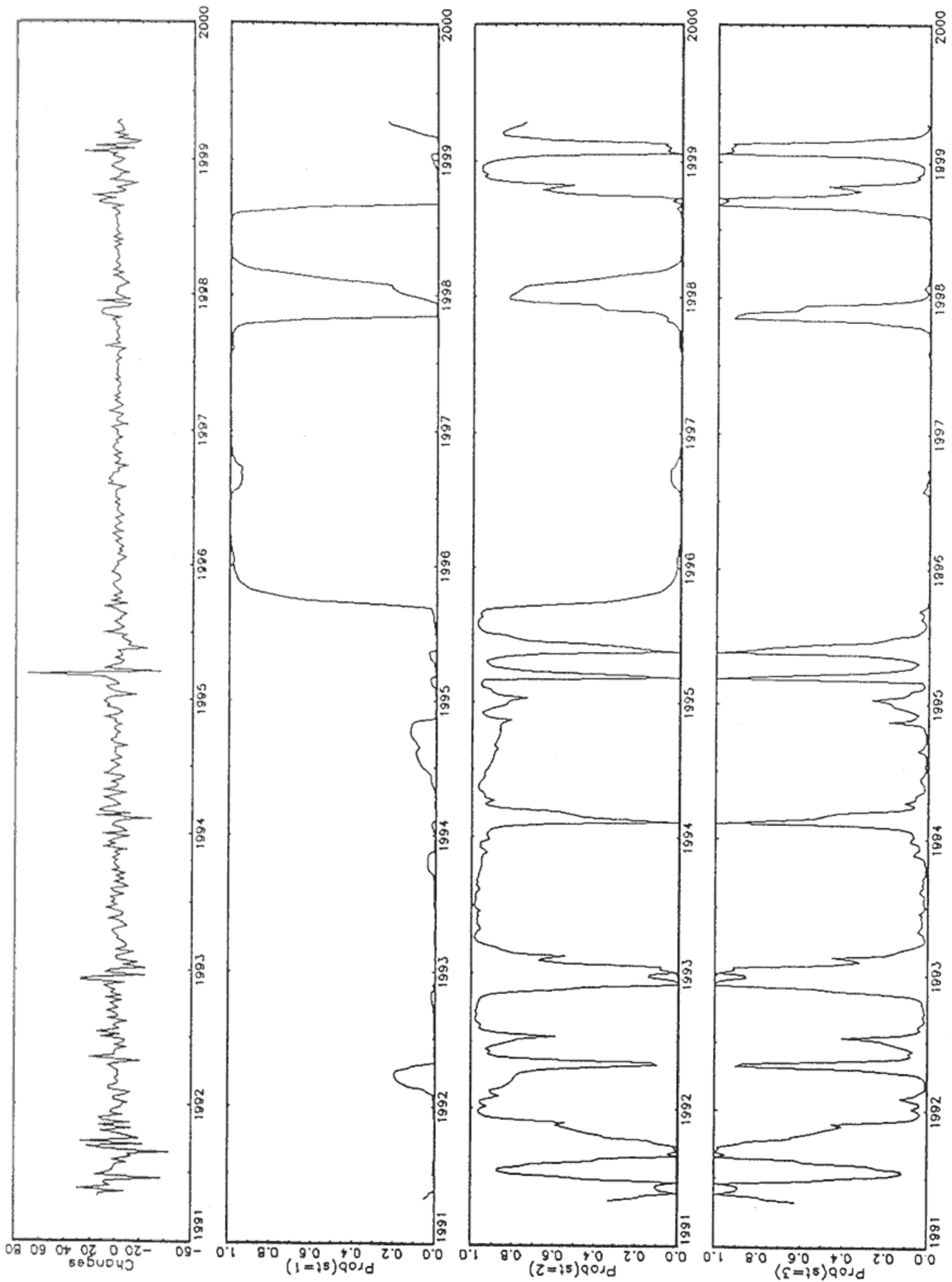


FIGURE 6: ARG -INT RATES (USSD) - SWARCH(3,2)

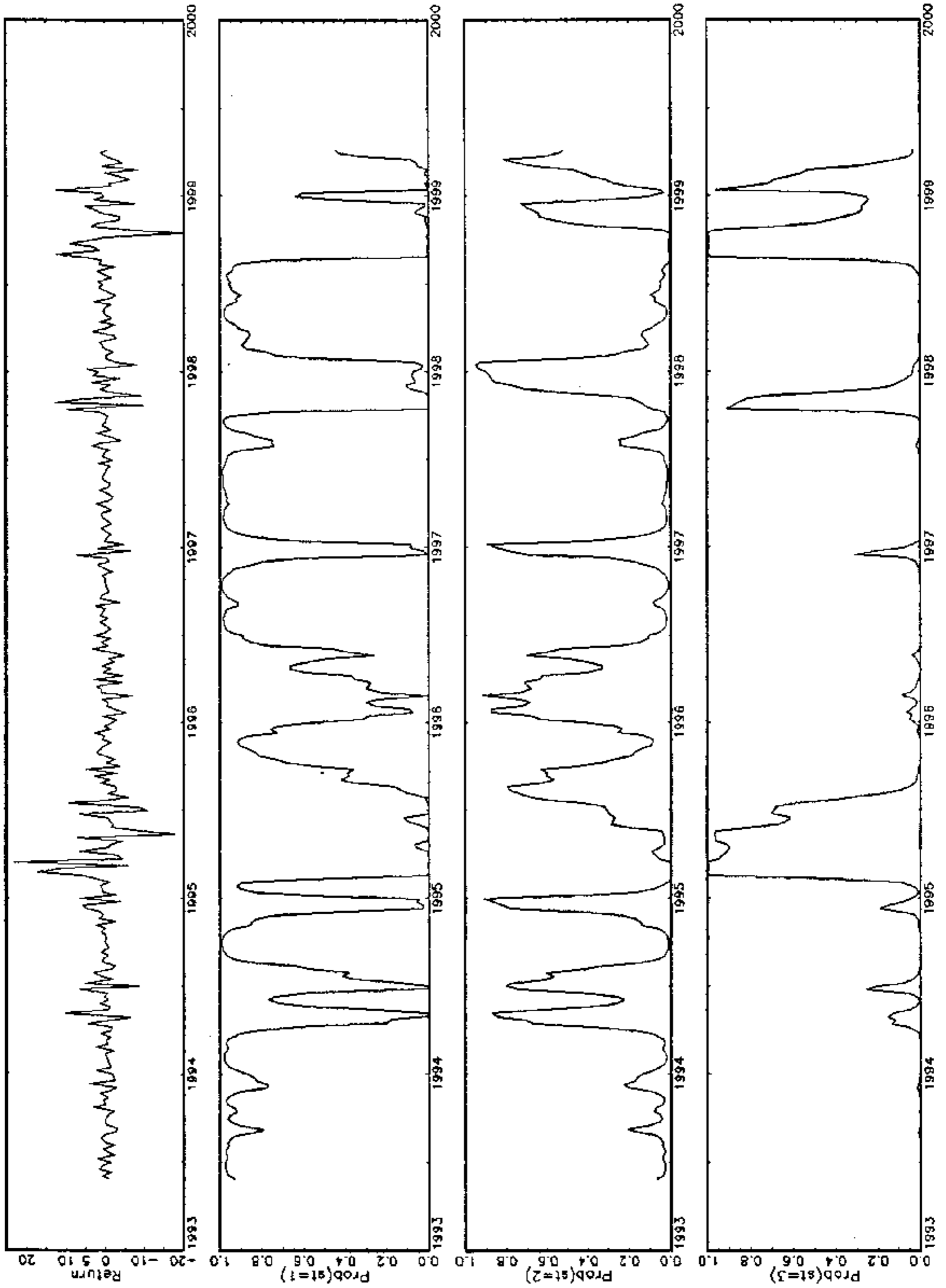


FIGURE 7: ARG -INT RATES (ARS) - AR(1) 3-STATE MEAN SWITCHING

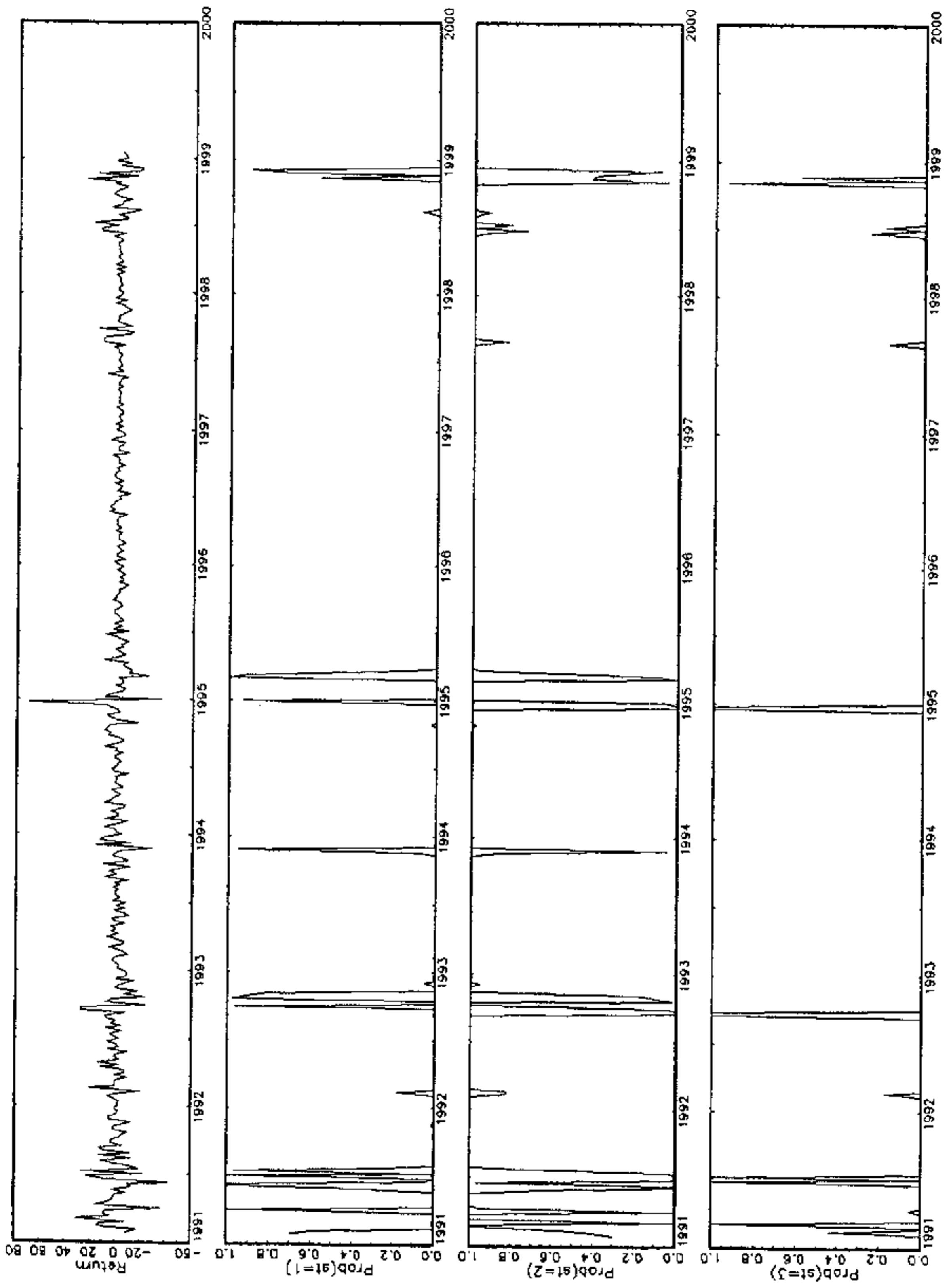


FIGURE 8: ARG -INT RATES (ARS) - AR(1) 3-STATE MEAN-VAR SWITCH

