Financial Liberalization and Emerging Stock Market Volatility

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Abstract

In this paper we review the factors that may lead to structural changes in stock market volatility and present an analysis that assesses whether emerging stock market volatility has changed significantly over the period 1976:01-2002:03. This period corresponds to the years of more profound development of both the financial and the productive sides in emerging countries. We use alternative methodologies of endogenous breakpoint detection that estimate the dates at which the behavior of stock market volatility changed. The analysis suggests that volatility has behaved in a different manner over the period.

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1 Introduction

Since mid 1980s most of the emerging countries were involved in financial markets opening and stock markets liberalization process. According with finance theory, stock market volatility should increase or decrease when markets are opened (e.g., Bekaert and Harvey 1997, 2003a,b). On the one hand, markets may become informationally more efficient leading to higher volatility as prices quickly react to relevent information or speculative capital may induce excess volatility. On the other hand, in the pre-liberalization process, there may be large swings from fundamental values leading to higher volatility. In the long run, the gradual development and diversification of the markets should lead to lower volatility.

Considerable research has focused on stock market liberalization and stock market volatility (e.g.,Bekaert and Harvey 1997, Bekaert, Harvey and Lumsdaine 2002a, Kassimatis 2002, De Santis and Imrohoroglu 1997, Huang and Yang 1999, Kim and Singal 2000, and Aggarwal et al. 1999) and the empirical evidence is mixed. For example, Bekaert, Harvey and Lumsdaine (2002a) show, in the standard mean variance framework, that prices under integration are decreasing in the covariance between world and local flows whereas in a segmented world, only local cash flow volatility matters for pricing. Given that the volatility of emerging market returns is much higher than the covariances with world market returns, this model suggests that stocks prices will jump on the announcement of a liberalization and expected returns will decrease. The size of the jump should be related both to the credibility of the government's announcement - and policies in general - and to the diversification benefits to be gained from integrating the market. In related work, De Santis and Imrohoroglu (1997) study the behavior of volatility in some emerging countries and the effect of liberalization of financial markets. They find significant evidence for time-varying volatility and different effects of liberalization on volatility across countries. Specifically, they find that volatility decreased after liberalization in Argentina. Huang and Yang (1999) analyze the impact of financial liberalization on stock price volatility in ten emerging markets. Taking as reference the dates of financial market liberalization from De Santis and Imrohoroglu (1997), Huang and Yang (1999) show that the unconditional volatility of the stock markets in three of the countries analyzed (South Korea, Mexico and Turkey) increased after liberalization, whereas it significantly decreased in another four countries (Argentina, Chile, Malaysia and the Philippines). However, the conditional volatility of the markets of Brazil, Korea, Thailand and Turkey experienced a significant increase while that of the remaining six markets experienced a decrease after liberalization. In a recent paper, Kim and Singal (2000) analyze changes in the level and volatility of stock returns around the opening to international capital markets. The results reveal that opening of the markets is good for domestic investors: Stock prices rise while the volatility tends not to increase. They find, though, that Argentina did experience high volatility around the market opening and Mexico had a short period of high volatility prior to market opening. The three latter papers take the dates of the structural changes as given, and then proceed to analyze the behavior of volatility pre and post-change. Aggarwal et al. (1999) follow a different route and, instead of specifying a priori the dates of the breaks, they detect shifts in volatility from the data by using an iterated cumulative sum of squares (ICSS) algorithm. This procedure identifies the points of shocks or sudden changes in the variance of returns in each market and how long the shift lasts. Once the dates of the shifts are located, they identify the events that are associated with the changes in volatility. They examine ten of the largest emerging countries in Asia and Latin America, in addition to Hong Kong, Singapore, Germany, Japan, the UK and the US. Furthermore, they include a few regional indexes calculated by several investment banks and rating companies. The findings suggest that most events around the time period when shifts in volatility occur are local (the Mexican peso crisis, periods of hyperinflation in Brazil and Argentina, high trade deficit in South Korea, etc.). The results also show an interesting statistical finding. In sixteen of the twenty series ARCH and GARCH effects are both significant. However, when the dummy variables that identify the breakpoints are introduced in model, the GARCH coefficients become nonsignificant.[1]

In this paper we focus on one aspect of the stock market evolution, and analyze whether stock market volatility has changed significantly over the period 1976:01-2002:03 for six emerging countries . The choices of countries and period make the analysis especially relevant. Our sample corresponds to a period that includes most of the liberalization and privatization processes in these emerging countries. We attempt to ascertain, then, if significant changes in the structure of stock market volatility happen through time, and, more relevantly, we try to locate the dates of these changes so we can identify the possible events that led to these changes. We start by doing a simple graphical analysis of the evolution of a rolling measure of stock return volatility.

The rolling variances give evidence of the existence of time structure of a typical ARCH-type, that identifies periods of increased conditional volatility. It is also noticeable that the unconditional level of the volatility changes over time. This points at the existence of structural changes or breakpoints in the statistical model generating return volatility, and we proceed to try to identify these changes. Given that we do not want to impose the dates of the breaks, we use alternative methodologies based on the estimation of endogenous breakpoints. Moreover, the richness of the period analyzed raises the possibility of there having been more than one structural break over such a long and eventful period. Thus, an approach that allows for multiple breaks in the series seems to be warranted. First, we initially opt for the estimation of a (still unspecified) number of structural breaks, following the procedures suggested by Bai

[1] This finding is not easy to interpret. The fact that the breaks are detected by using cumulative sums of squares makes it likely that big returns are causing the appearance of the break. If then a dummy variable is included for the whole period until the next break (i.e. until the next big return signals a break) then it is clear that the ARCH effect (the increase in variance when a big return appears) will be accounted for by the period-by-period dummies. Thus, their conclusion that the persistence in the variance disappears when accounting for the breaks may be misleading. We find some evidence of changes in the ARCH and GARCH effects of the models that include breaks, but not always in the direction of losing significance.

and Perron (1998, 2002a,b) and already successfully applied by Bekaert, Harvey and Lumsdaine (2002a,b) to investigate multiple structural changes in the stock markets of emerging economies. We then test for robutness of our results by using two additional test for endogenous breaks in volatility (Kokoszka and Leipus 2000 and Inclán and Tiao 1996).

The structure of the paper is as follows. Section 2 explains the main factors that cause changes in stock market volatility. In Section 3, we present a first look at the volatility behavior in some emerging markets. Section 4 analyzes emerging stock market volatility by locating the structural breaks and identifying the relevant economic or political events that occurred simultaneously to these changes. Section 5 concludes.

2 The Relevance of Stock Market Volatility

While there is general consensus on what constitutes stock market volatility and, to a lesser extent, on how to measure it, there is far less agreement on the causes of changes in stock market volatility. One should first ask whether it is the conditional volatility that changes - in the way implied by ARCH-type models, or by the volatility in levels framework in Lamoreux and Lastrapes (1990) - , that is, the volatility given a specific realization of past returns or of other relevant variables, or whether it is the unconditional volatility that changes, in what would have to be considered a change in the data generating process. As a matter of fact, all the reasons we review in this Section can be consistent with changes in conditional volatility - for example, volatility tends to increase significantly after an unusually big negative return, which would be evidence of "incoming bad times" for the company that might last for a few periods - but also with changes in the unconditional volatility - this unusually negative return might signal the beginning of the final decline in the business conditions of some company or it may have been triggered by a change in consumer preferences that will have permanent effect on that specific company.

Some economists see the causes of volatility in the arrival of new, unanticipated information that alters expected returns on a stock (Engle and Ng, 1993). Thus, changes in market volatility would merely reflect changes in the local or global economic environment. Others claim that volatility is caused mainly by changes in trading volume, practices or patterns, which in turn are driven by a number of factors including changes in macroeconomic policy, shifts in investor tolerance of risk and increased uncertainty.

More recently, researchers have noticed a fundamental shift in investor behavior, which has led to the abandonment of the efficient market hypothesis in favor of behavioral finance. According to Shiller (2000) stock prices in the last few years - prior to the bursting of the dot-com bubble - were too high and volatile to be explained by fundamentals: Investor behavior seemed to be driven less by fundamental variables and more by other factors that led to higher and sustained volatility. Among these, Shiller mentions sociological and psychological factors - US triumphalism, cultural changes favoring business success, the impact of baby boomers in the market - as well as behavioral factors directly related to trading practices - increasingly optimistic forecasts by analysts, the enormous expansion of trading volume and an increase in the frequency of trading. These researchers would explain changes in market volatility as mainly determined by changes - temporary, as in the dot-com frenzy, or permanent, as in the generalized surge in interest for the stock market of recent years - in investor behavior.

Other factors that have been identified by researchers as leading to changes in market volatility are the improved speed and efficiency with which financial transactions are carried out, the increased interdependence and interconnectivity of markets and the greater homogeneity of investor behavior. All these factors are related to the speed at which the market accommodates shocks and incorporates the relevant information into the prices. Thus, it could be argued that they may lead to a higher level of volatility but to different characteristics of volatility dynamics. For instance, persistence of volatility may change: A market where the information gets incorporated faster into the price must revert to the "normal" level of volatility faster, and thus it must have a reduced persistence of volatility shocks. These factors driving changes in volatility would correspond, therefore, to the stage of development of the domestic stock market and to its degree of integration with other markets.

We focus our analysis therefore on characterizing the dynamic evolution of volatility in six emerging stock markets data and on placing that evolution in the context of the historical events related to the development of the economy in both its productive and financial sides. The next Sections develop the methodologies we use and present the results of our analysis.

3 Volatility Behavior in Some Emerging Stock Markets: A First Look at the Data

The last couple of decades have witnessed a substantial development of financial markets, both in developed countries, some of which did not fully liberalize capital flows until the 1990s, as it was the case of European Union countries, and in emerging countries. The case of emerging countries is especially interesting, given that economic development has gone hand in hand with financial market development. Thus, these countries provide with a natural experiment on the effects of relevant economic and political events on the stock market, and viceversa. It is no surprise, then, that research on the interplay between the real side of the economy and the financial side has advanced quite substantially in the last years, mostly profiting from analyses based on emerging markets. Given the recent history of financial crises in developing economies, that have sometimes spilled over to developed economies and had caused real effects in both developing and developed, a deep understanding of the factors that affect financial markets becomes of extreme priority.

In this Section we analyze the evolution of the behavior of stock market volatility in a selected set of emerging markets. Our dataset consists of six monthly series of stock market prices, obtained from the Emerging Market Indexes database of Standard & Poor's, formerly calculated by the IFC, that cover the period from 1976:01 to 2002:03. The countries chosen are Argentina, Brazil, Chile, Korea, Mexico and Thailand. The choice of countries has been mainly determined by data availability, for these were the countries for which the complete series of the index, starting in 1976, was available . We first resort to a simple graphical analysis. Then we move into more complete statistical analyses, where we first allow for the existence of conditional heteroskedasticity over time (by using a simple GARCH model) and we then allow for unconditional heteroskedasticity by identifying structural breakpoints in the volatility series.

Table 1 reports basic univariate statistics for the (annualized) stock returns of our six markets. As said before, the data run from January 1976 through March 2002, thus yielding a total of 315 observations. The statistics included in the table are the average return, standard deviation, skewness coefficient, kurtosis coefficient, first order autocorrelation coefficient, a Ljung-Box test for significance of the first four autocorrelations, an ARCH-LM test with four lags for existence of conditional heteroskedasticity and the Jarque-Bera test of normality.

Average returns range between 1.4% in Brazil and 15.2% in Chile. In terms of standard deviation (volatility), the markets in Argentina and Brazil have been the most volatile while Chile and Thailand seem to have the most stable markets. The coefficients of skewness and kurtosis reveal nonnormality in all countries. This result is confirmed by the Jarque-Bera normality test for all countries. The Ljung-Box Q-statistics along with the autocorrelations indicate significant autocorrelations in Chile, Mexico and Thailand. The LM-ARCH(4) univariate tests reveal ARCH effects for our six emerging economies. So far, all these results were to be expected, and they do not add much new evidence to results already known.

[Insert Table 1 here]

In the upper panel of Figures 1a-6a we show the evolution of the stock returns of each country during the period 1976:01-2002:03. In order to provide a first look at the time evolution of stock market volatility we use a simple graphical device and include in the middle panel a nonparametric measure of volatility (a 12 month rolling variance of returns). This annualized rolling variance is calculated as follows:

$$\sigma^2(r_t) = \left[\sum_{k=1}^{12} (r_{t-k} - \mu_{12})^2 /11\right] \tag{1}$$

where r_t is the return[2] of the stock market index over period t and μ_{12} is the sample mean over the 12 month window.

[2] We calculate returns as $12(\log P_t - \log P_{t-1})$.

Visual inspection of this nonparametric variance gives a first idea of the evolution of the conditional variance of the different stock markets. In general, one can see that the variance changes over time and the different markets are subject to both unstable and stable periods, where the variance changes due to different events (news) that shock the markets. This of course reflects the already standard ARCH type effects that most financial series present: The coming of news to the market affects the variance of the market (ARCH effect), and this effect in the variance tends to persist over time (GARCH effect). We include in the lower panel of Figures 1a-1f the conditional variance of returns estimated by fitting a simple GARCH(1,1) model, with an AR(1) in the mean equation, to the stock returns, using the full sample from January 1976 through March 2002 for each of the six emerging countries.

Given a simple GARCH(1,1) process, the stock returns and the variance of innovations to stock returns are given by:

$$\begin{aligned} r_t &= \beta_0 + \beta_1 r_{t-1} + u_{t-1} \qquad u_t \longrightarrow iid(0, \sigma_t^2) \text{ [Mean equation]} \\ \sigma_t^2 &= \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2 \text{ [Variance equation]} \end{aligned} \tag{2}$$

Once the parameters have been estimated, usually by QML estimation (Engle, 1982; Bollerslev and Wooldridge, 1992), a series of fitted values of the conditional variance can be generated by recursively evaluating the formula $\sigma_t^2 = \widehat{\varpi}_0 + \widehat{\alpha}_1 \sigma_{t-1}^2 + \widehat{\alpha}_2 u_{t-1}^2$, starting with $u_0 = 0$ and $\sigma_0^2 = \widehat{\varpi}_0/(1 - \widehat{\alpha}_1 - \widehat{\alpha}_2)$.

We comment now on the results for the different countries, trying to put emphasis on the political or economic events that may have led to noticeable stock market instability or to large negative returns.

[Insert Figures 1a-6a here]

The rolling variance for Argentina (Figure 1a, middle panel) shows the evolution of the volatility of Argentine returns. There have been three important negative returns in the Argentine stock market returns, dated in 1976, 1989 and 1990, that come associated with unstable periods. A significantly volatile period was concentrated on 1985 when the Austral plan was introduced in order to fight against hyperinflation.[3] However, the most volatile period corresponds to the years 1989-1990, where sustained hyperinflation and currency depreciation eventually led to the pegging of the Argentine currency to the US dollar. A look at the rolling variance shows that the average level of volatility is markedly reduced from that moment on: That is, the Argentine stock market is still subject to changing volatility - conditional heteroskedasticity - but the average (unconditional) level of the volatility seems to have decreased significantly with the pegging of the currency. One could then expect to find a structural break in the variance of the stock market around the time of the fixing of the exchange rate (see Appendix 1 for a detailed chronology of liberalization process and other relevant macroeconomic events for our six emerging countries).

[3] Aggarwal et al. (1999) found similar volatile periods in Argentina, Brazil, Mexico, Korea, Mexico and Thailand.

In Brazil, we detect a very negative stock market return in 1990, a period which coincided with an anti-inflation plan, the confiscation of deposits, the introduction of a new currency and presidential elections. The rolling variance (middle panel of Figure 2a) shows a slow but continuous increase in the volatility until period 1990-91, when it reaches its highest level. Since then, the volatility follows a downward trend by which it returns to lower levels comparable to those at the beginning of the sample. During the period 1989-1991 several anti-inflation plans were adopted and confiscation of financial assets took place. The clear upward trending behavior in the variance seems to give support to the need of the stabilization plan, which succeeded in bringing the volatility of the stock market down to levels comparable to those of the early 1980's. Except for that obvious change in the trend, there does not seem to be further evidence of structural changes in the Brazilian variance. We advance now that a structural break in a GARCH process will not detect this behavior, since what seems clear from the picture is that it is a change in the time trend of volatility. That is, in order to detect the change in variance behavior for Brazil one would include a time regressor in the variance equation, and allow for that coefficient to change at the break. A look at the fitted conditional variance from the simple GARCH(1,1) model (Figure 2a, lower panel) shows that the upward trend and its subsequent change can be captured quite well by the GARCH specification: It seems therefore that the trend in the variance comes from a succession of increasingly big returns (negative or positive) and a high persistence of the variance whereas the posterior decrease comes from the returns stabilizing. The GARCH model captures that evolution without resorting to a structural break and no further evidence of breaks in the variance behavior can be derived from the graphs.

The rolling variance for Chile (Figure 3a, middle panel) shows that the average level of volatility seems to have gone through three different periods. First, we encounter a period of high volatility during 1976-1979. After 1979 - during the Tablita Plan - and coinciding with the first opening of the market to international capital flows, average variance drops significantly in a structural break manner. Then a period of relatively low variance follows. Finally, after 1995 the variance seems to fall again in what could be considered - although not as clearly - a second break. It can be seen in the lower panel that the GARCH specification in the case of Chile is unable to track correctly the evolution of the rolling variance: Given the three periods of increasingly lower volatility, the GARCH model, which cannot handle structural breaks, yields a fitted variance that follows a downward trend, as if it were smoothing out the three periods, obscuring the fact that the reduction in Chilean stock market variance seems to be, more than a continuous process, a once and for all (or maybe twice and for all) phenomenon.

In the case of the Korean stock market returns, one can see that the major unstable period happened during the Asian crisis in 1996-1997. The oscillations of the returns are not very high during the full sample, until we reach 1996-1997, where a big increase in volatility seems to have occurred. The rolling variance agrees with this evidence: The average level of volatility is fairly constant until

1997 when the Asian flu disrupted Asian financial markets. The variance, however, seems to be returning, in the last dates of the sample, to pre-crisis levels. The GARCH specification tracks the evolution of the Korean variance quite well, and, except for the Asian crisis phenomenon, which could be interpreted as a structural break or as merely the consequence of a extremely negative return, there does not seem to be clear evidence of a change in the behavior of the variance (see Figure 4a, middle panel).

Mexico presents some interesting facts. The rolling variance shows that the average level of stock market volatility is low, except during the four unstable periods that followed four major negative returns in 1983, 1987-88, 1994-95 and 1998. The highest volatility level occurred during the years 1987-88, during which anti-inflation plans were being implemented in Mexico. The second largest shock, and unstable period, corresponded to the Tequila crisis, in 1994-1995, when the Peso collapsed and a (short) period of intense political and economic turmoil followed. A comparison between the rolling variance and the GARCH estimated variance shows that the latter closely approximates the former, but there seems to be a level effect in the GARCH estimate: Average variance estimated by the GARCH model is higher throughout the whole sample. This is probably due to the four periods of instability. It seems that Mexican stock market instability is very short-lived, that is, it has very low persistence. This is clear in the rolling variance, which shows how after the shocks die out, and they do so quickly, the variance returns to very low levels. No clear evidence of breaks is apparent in the graphs, where the periods of instability seem to be induced by big negative returns with the market returning quickly to pre-shock levels (see Figure 5a, middle panel).

Thailand shows a most interesting evolution. The rolling variance, and also the GARCH specification, which seems to be capturing the behavior of volatility quite well, separate the sample in three periods. The first, of extremely low variance and where no significant "bad news" are present, runs from the beginning of the sample until around 1987-88. In this period, that coincides with the official date of financial market liberalization in Thailand (see Appendix 1) a big negative return seems to provoke the average level of the volatility to increase, after which more frequent big returns give rise to jumps in the variance that are relatively short lived. Then the Asian crisis in 1997 seems to throw the Thailandese market into a frenzy of high variance with constant up and down fluctuations. It can be seen, however, that the GARCH model tracks quite well the behavior of variance after the crisis. Thus, the graphs give evidence for one or maybe two structural breaks in the behavior of the volatility of the Thailandese stock market. The first break would coincide with the liberalization of the stock market (that yields an increase in the average level of the variance) and the second, a little more unclear, would coincide with the Asian crisis.

We have already commented on the results of the GARCH models as we proceeded through the section. It can be seen that the evolution of the rolling variance closely approximates the estimates of the conditional variance from a GARCH(1,1) model, this being especially noticeable during periods of high volatility (see, e.g., Schwert 2002). In other words, we find evidence of conditional heteroskedasticity in emerging stock markets, by which volatility is a positive function of both past volatility (persistence, or GARCH effect) and past innovations to the return process (the "news," or ARCH effect). This result was, of course, to be expected, and it adds very little to what has already been found in other analyses of the emerging stock markets, and of most stock markets for that matter. However, it can also be seen that the GARCH-fitted variance fails to track some of the once and for all changes in behavior of the variance and instead smooths out those changes over the whole range of the sample (this is especially noticeable for Chile, but there is some evidence for the other countries as well). Thus, there seems to be evidence of structural breaks (i.e. one-time changes in the process generating the variance) that cannot be properly accommodated by a model of varying conditional variance, and we turn now to an analysis that tries to detect these changes.

4 Structural Breaks in Emerging Stock Market Volatility

We have provided in Section 2 a justification of the importance of gaining a thorough understanding of stock market volatility and in Section 3 we have carried out a first look at the evolution of this variable in a number of emerging countries. We are interested now in detecting the events that may have had led to changes in the volatility of emerging stock markets. Some recent contributions have looked for structural changes in the behavior of emerging stock markets, and on detecting the causes of these changes, making special reference to episodes of financial liberalization and economic policy decisions.

In this paper, we try to assess the evidence for structural changes in the process that generates stock market volatility, that is, the evidence for changes in unconditional volatility. These changes are manifest in changes in the level of conditional variance, measured by the intercept of the variance equation in a GARCH model, and in changes in the persistence of conditional variance, as measured by the autoregressive parameter in the GARCH equation α_1, or by the sensitivity of variance to innovations to the return process, as measured by the ARCH parameter α_2. We use techniques for the location of endogenous structural breaks to try and locate the time of the change in the parameters of a GARCH variance equation without imposing these dates a priori. Our choice of a GARCH specification for the modelling of the variance was determined both for its simplicity and its ability to replicate the features of conditional volatility. Ever since the rise of GARCH models, where the volatility of an asset is allowed to be persistent and affected by the size of past innovations, these models have been successfully applied to financial data and have become the most popular tools to study financial market volatility. Pagan and Schwert (1990) show that the GARCH model performs quite well in comparison with many alternative methods for modelling conditional volatility of stock returns. Most recently, Schwert (2002) used a GARCH(1,1) to model conditional variance for the Nasdaq.[4]

Given the simple GARCH(1,1) process in (2), we try to capture the changing behavior in the volatility of the stock markets of our six emerging countries by proposing alternative GARCH(1,1) specifications where we allow for breaks in the parameters in the variance equation.[5] We explain in the next subsection the methodology followed to detect the endogenous breaks in the variance process. The process followed is sequential: That is, starting from a simple GARCH(1,1) model without a break, we test for the existence of a break either in the intercept ϖ_0 or in all three parameters of the variance, $\varpi_0, \alpha_1, \alpha_2$. If the null of no break can be rejected, then we test for existence of a second break, and so on. Finally, we test for robustness of our results by using two additional test for endogenous breaks in volatility (Kokoszka and Leipus 2000 and Inclán and Tiao 1996).

4.1 Locating Structural Breaks

The location of endogenous structural breaks in time series has been a matter of intense research in the last few years: One need only take a look at Banerjee, Lumsdaine and Stock (1992), Ghysels, Guay and Hall (1997), Bai, Lumsdaine and Stock (1998) or at the papers in the special issue on structural change of the *Journal of Econometrics* (edited by Dufour and Ghysels, 1996) to realize that the topic is still in its early development stages. The issue of estimation of the number and location of multiple endogenous structural breaks is also being an active field of research and results on the procedure and properties of the tests involved are now being published. Papers by Andrews, Lee and Ploberger (1996), García and Perron (1996), Bai (1997, 1999), Lumsdaine and Papell (1997) or Bai and Perron (1998, 2002a,b) are some of the most relevant examples.

Most of the techniques in the above papers have been developed for estimation and location of endogenous breaks in the mean parameters of trend models. However, as Bai and Perron (1998) mention, they can also accommodate changes in the variance. Given the richer structure of the GARCH variance process, we have to be cautious about how immediately these tests can be extended to changes in the GARCH parameters. In this paper we use the critical values and limiting distributions of the tests for changes in the mean parameters but warn in advance that further results on the asymptotic distributions of our tests might modify the critical values or limiting distributions to be used. Therefore, with this caveat in mind and notwithstanding the fact that some of the results, such as the expression for the calculation of a confidence interval for the breakpoint cannot be directly applied, we use the general framework in Bai and Perron (1998, 2002a,b) and their procedure of sequentially locating the breaks with its associated critical values.

[4] See Bollerslev and Kroner (1992) for an exhaustive review of this literature.

[5] Pagan and Schwert (1990) and Pagan (1996) note that it is usually enough with a GARCH(1,1) model to account for most of the time structure in conditional variance. Except maybe for an asymmetric leverage effect, most series we are aware of can be conveniently explained by a GARCH(1,1) model.

This sequential procedure consists of locating the breaks one at a time, conditional on the breaks that have already been located. Thus, we locate the first break and test for its significance against the null of no break. If we reject the null, we then look for the second break conditional on the first break being the one already found, and test for the existence of a second break conditional on the first one, and so on.

The general framework consists of a model for stock market returns of the form in (2) where l breaks exist in the variance process. That is, there is a set $\mathbf{t} = \{t_1, t_2, ...t_l\}$ of points in time where the process generating the variance - in this case, the parameters ϖ_0, α_1 and α_2 - has changed.

Given this set $\mathbf{t}$ of l points in time at which q of the parameters of the process change, we want to test if there is an additional break and, if so, when the break takes place and the value of the parameters before and after the new break. The likelihood of the model that contains the l breaks in $\mathbf{t}$ is specified as $L(\mathbf{t}, \theta)$. θ is the set of all parameters and it contains both the parameters that do not change over time and the l values of each of the q parameters allowed to change at the breakpoints. In our specific model, and disregarding some constants,

$$L(\mathbf{t}, \theta) = -\frac{1}{2}\left\{\sum_{t=1}^{t_1}\left[\log \sigma_{1,t}^2 + \frac{u_{1,t}^2}{\sigma_{1,t}^2}\right] + \sum_{t=t_1+1}^{t_2}\left[\log \sigma_{2,t}^2 + \frac{u_{2,t}^2}{\sigma_{2,t}^2}\right] + ... + \sum_{t=t_l}^{T}\left[\log \sigma_{l,t}^2 + \frac{u_{l,t}^2}{\sigma_{l,t}^2}\right]\right\} \tag{3}$$

where $u_{i,t} = r_t - \beta_{0,i} - \beta_{1,i} r_{t-1}$ and $\sigma_{i,t}^2 = \varpi_{0,i} + \alpha_{1,i}\sigma_{t-1}^2 + \alpha_{2,i}u_{i,t-1}^2$.

The alternative model is specified as one which contains an additional break at time τ. Thus, the set of $l+1$ breakpoints becomes now $\mathbf{t}^* = \{\mathbf{t}, \boldsymbol{\tau}\}$, and the log-likelihood associated with the alternative model is $L(\mathbf{t}^*, \theta(\mathbf{t}^*))$. The procedure of detecting and timing the break consists in finding the series of likelihood-ratio statistics of the alternative (unrestricted model) of $l+1$ breaks against the null (restricted model) of l breaks:

$$LR_\tau(l+1 \mid l) = -2\left[L\left(\mathbf{t}, \widehat{\theta}(\mathbf{t})\right) - L\left(\mathbf{t}^*, \widehat{\theta}(\mathbf{t}^*)\right)\right] \tag{4}$$

where $\mathbf{t} = \{t_1, t_2, ...t_l\}$ is the first set of l breaks (under the null of no additional break) and $\mathbf{t}^* = \{t_1, t_2, ...t_{l+1}\}$ is the set of $l+1$ breaks that includes τ as a new possible time for a break. $L\left(\mathbf{t}, \widehat{\theta}(\mathbf{t})\right)$ is the value of the log-likelihood of a model that includes the breaks in $\mathbf{t}$, where $\widehat{\theta}(\mathbf{t})$ are the ML estimates of all the parameters of the model. The new breakpoint is located by using the $\sup LR$ test:

$$\sup LR : \sup_{\tau \in \mathbf{T}^*} LR_\tau(l+1 \mid l) \tag{5}$$

where $\mathbf{T}^*$ is the set of possible times for the new break. Given the series of LR tests and the $\sup LR$ test, the date of the new breakpoint $\widehat{t}$ is

$$\widehat{t} = \arg\max_{\tau \in \mathbf{T}^*} L\left(\mathbf{t}^*, \widehat{\theta}(\mathbf{t}^*)\right) = \arg\max_{\tau \in \mathbf{T}^*}\left[\sup LR_\tau(l+1 \mid l)\right] \tag{6}$$

If the sup LR test is above the critical value, then the null of no additional breakpoint is rejected and the date for the new breakpoint can be estimated to be $\widehat{t}$. The values of the parameters before and after the break correspond to the estimates in $\widehat{\theta}(\mathbf{t}^*)$. The different versions of this statistic (Bai, Lumsdaine and Stock 1998, Bai and Perron, 1998, 2002a,b) have a limiting distribution that depends on a q dimensional Brownian motion, where q is the number of parameters allowed to change at the time of the break. Thus, the critical values of the $LR(l+1 \mid l)$ test depend on l and on q (e.g., Bai and Perron, 1998). These values are found by simulation of the q dimensional Brownian motion.

One final comment is that $\mathbf{T}^*$, the set of possible times for the break, must exclude a number of observations around the initial and final dates and around the dates in $\mathbf{t} = \{t_1, t_2, ...t_l\}$ that ensures that each subperiod defined by the breakpoints contains enough observations for the parameters to be accurately estimated. In our analysis we have used a trimming proportion of 0.15.[6] That is, we start by locating the first breakpoint in $\mathbf{T}^* = \{0.15T, 0.85T\}$ and then every time we locate a new breakpoint, we exclude from $\mathbf{T}^*$ the 15% observations to both sides of the last breakpoint estimated.

Notice that the procedure outlined above could be considered a *sequential* location of breakpoints. That is, given that $\mathbf{t} = \{t_1, t_2, ...t_l\}$ is the set of l estimated breakpoints, the $(l+1)^{th}$ breakpoint is located conditional on the other l (e.g., Bai, 1997, or Bai and Perron 2002a, b). An alternative way of locating multiple breakpoints (Bai and Perron, 1998) would compare the value of the likelihood for the l estimated breakpoints with that of all possible partitions of the sample that come from a model with $(l+1)$ breaks. This "simultaneous" location of all breakpoints may lead to different inferences about the breakpoints, but it also yields consistent estimates of the breaks.

The critical values, both for the simultaneous and the sequential version of the test have been tabulated by the authors, and are available in their papers. We present those critical values for the sup $-LR$ test for one and two breaks in three parameters in Table 2.

[Insert Table 2 here]

These tests can consistently estimate not the *dates* of the breaks but the *proportion* of the total sample at which the breaks occur. That is, we estimate consistently that the break happens at "around the 0.2 quantile" of the sample. Of course, one can then back up the specific time of the event, given a fixed number of observations T in the sample.

4.2 Empirical Results of the Endogenous Break Analysis

We present now the results of our analysis of whether the stock market volatility in our six emerging markets of interest has changed significantly over the period

[6] This proportion is usually taken to be 0.15 or 0.1. This means that we will use only 70% of the observations, discarding the 15% at the beginning and the end of the series, for the first break and then approximately 40% and 10% for the second and third breaks respectively.

1976:01 to 2002:03. We comment on the six countries separately, and include for each country a figure which shows the fitted conditional variance of the final model we adopt after the break estimation.[7] We use this final fitted variance to assess how well the final model is capturing the variance of that specific stock market. Given the nonparametric rolling variance in Figures 1c-6c (lower panel), the estimated conditional variance coming from a parameterized model should closely reproduce the nonparametric estimate. Thus, we use a visual analysis of the estimated conditional variances of the different models to gain some intuition of their validity.

The main results can be summarized as follows. First, we detect for most of the emerging countries that there have been structural changes in their stock market volatility. Most of the countries present evidence of a single break, whereas Brazil seems to present no break and Mexico shows evidence of two breaks.

Second, the Asian flu in 1997 is the only date associated with possible breaks in several of the countries (Argentina, Chile, Korea, Mexico and Thailand). However, only for Korea the break detected is significant, whereas for the rest of the countries 1997 comes as an apparent candidate for a second (or third, in the case of Mexico) but the value of the $\sup -LR$ test does not allow to reject the null of no break. In other words, only Korea seemed to be truly affected in a structural manner by the Asian flu, whereas the rest of the countries experienced momentary instability (which led in most cases to the existence of a few big returns around that date) but the behavior of their market did not change significantly. Notice that this result is in contrast with usual findings of structural changes in volatility around 1997 (Aggarwal et al., 1999), that are probably caused by the outlying returns around the date of the crisis.

As we can see in Appendix 1, most of the countries went through a liberalization process during the 1980s.[8] A particular interesting result from our analysis is that for most of the countries the dating of the breaks in the volatility behavior tend to correspond with liberalization processes or with significant monetary events that are particular to the country, and not to external instability. In other words, as we have commented with respect to the Asian flu, all markets seemed to be momentarily affected, but only Korea truly showed a lasting effect. The rest of the countries have been mostly affected, in a structural manner, by their own particular economic events, whereas external events have tended to create only short lived instability.

We comment now on the results for each country. Parameter estimates are presented in Tables 3-5.

[7] An earlier version of this paper included one set of figures for every model estimated for each country. Each figure included the original series of returns, to facilitate a visual analysis, the series of LR tests for the different possible dates of the break, and the final estimated conditional variance coming from the model that incorporates the new break at the date of the $\sup -LR$ test. This yielded an excessive number of figures. Thus, we have opted for including only the fitted variance for the final model chosen for each country. All other figures and sequences of LR tests are of course available upon request.

[8] For a detailed chronology of financial liberalization in emerging countries see Bekaert and Harvey http://www.duke.edu/~charvey/Country_risk/couindex.htm.

[Insert Tables 3-5 here]

Results for Argentina can be seen in Table 4 and in Figure 1c. Argentina presents one single significant break, dated in March, 1991. This month is associated with ADR and the country fund introduction but, most importantly, with the decision of pegging the Peso to the dollar. The estimated parameter values - both when the break is allowed only in the intercept of the variance equation and when all parameters are allowed to change - confirm the fact that the volatility of the Argentine stock market was substantially reduced around 1991, falling by almost an order of magnitude. The Argentine market also seems to be less sensitive to news (α_2 falls to 0.04 from 0.4), that is, volatility is less intensely affected by the coming of new information: We have already found evidence of this effect in the nonparametric variance in Figure 1a, where it was clear that large (negative) returns had a substantial effect on the variance in the periods prior to 1991, but thereafter the market seemed to be much less sensitive to the appearance of news. Finally, volatility tends to be more persistent (α_1 increases, which means that more of the variance at time t gets fed back into time $t+1$). The Argentine market, therefore, seemed to profit extremely, at least in terms of stability, from the pegging to the dollar[9] and to start presenting signs of maturity, such as the reduced effect of news. Figure 1c gives evidence of the very good fit of the nonparametric variance provided by the model with the break.

[Insert Figure 1c here]

Brazil does not present any significant break, although there is clear evidence from Figure 2a of a trending behavior in the Brazilian market. Volatility increases consistently until around 1990-1991, when the stabilization plans where implemented, a new currency was introduced and the stock market was liberalized. Our procedure cannot locate a break in trending variance, but it is evident from the figure that around the date of liberalization the variance of the Brazilian stock market started to decline again and the market returned to old levels of low volatility. One can also see in Figure 1b that the simple GARCH model is already accounting quite well for the complete evolution of the variance. Figure 2c reproduces that same figure, given that there no significant break is detected.

[Insert Figure 2c here]

In the Chilean stock market only one significant break is detected, in 1983. After capital flows had been freed in 1979 and coinciding with the end of the

[9] At the time of the writing of this article, this finding may be surprising, given the deep crisis which Argentina is going through. It seems clear that Argentina's main problem was not the pegging of the peso, which indeed brought stability to the real and to the monetary sides of the economy, but mostly the lack of fiscal discipline that should have accompanied that peg, a few unfortunate events that spilled over to Argentina - such as the Asian flu, the devaluation of the Brazilian real, the foot and mouth disease that closed international markets to one of Argentina's main exports - and the strength of the dollar during those years.

Tablita plan and a second wave of privatization, the Chilean stock market witnesses a sudden drop in the level of the unconditional volatility. Notice that the numerical results for the change in intercept and for the change in all parameters (Table 3) are almost exact. However, the matrix of covariance of parameters could not be computed for the case of the break in all three parameters, we are led to think that the only change pertains to the level of the variance, and not to its persistence or the effect of news. Indeed, a look at Figure 3c shows how the model with the break in the intercept is providing a much better fit to the rolling variance than the model without a break and the model with a break in all three parameters, which completely misses the effect of news prior to 1983. Thus, volatility in the Chilean stock market was also significantly lowered by a stabilization plan and by the opening of the capital market. The official liberalization date, 1990, seems to be too late in the evolution of the stock market: The significant changes had already taken place long before that with the opening and stabilization of the economy.

[Insert Figure 3c here]

Korea presents a single significant break, at the time of the Asian crisis in 1997. In fact, it is the only country for which the Asian crisis seems to have had any significant long-lasting impact. Unconditional volatility increased substantially after the crisis, and the effect of news also increased, going from 0.07 to 0.27. Persistence of the variance, on the other hand, was significantly reduced. These are not good news for the Korean stock market. On the one hand, the market is subject to more intense average volatility, and the effect of new information has multiplied fourfold, which means that good or bad news tend to destabilize the market much more than they used to. The variance also changes more abruptly -lower persistence- (see figure 4c). All these are signs that point at the fact that investors are not confident at all in the Korean market. The market reacts wildly to new information and the variance itself tends not to persist at all, but it remains substantially sensitive to the arrival of news.

[Insert Figure 4c here]

In the Mexican stock market we date two significant breaks: November 1981 and around February-May 1988. We have found no clear event that may have led to the break in 1981. Volatility of the Mexican market increases markedly in that date, and the volatility also becomes more sensitive to news and less persistent, in a effect similar to that in Korea in 1997, although less dramatic. The second break, in 1988, corresponds to the liberalization of the financial sector and the beginning of the privatization process. At this time, the volatility of the market was reduced. The results in Table 5 show that the break corresponds only in the intercept of the equation (the $\sup -LR$ ratio is actually bigger for the one-parameter break than for the three parameter break) and the figures also show that the model that allows for a break in intercept is providing quite good a fit. In other words, we find for Mexico a similar effect to that in Chile, where at the time of the break the variance of the market gets reduced, but with no other significant change in behavior.

It is relevant to mention that, despite the evidence for an increase in volatility around the period of the Tequila crisis, no structural change seems to have happened at that time. The consequences of that crisis, which forced some major political and economic reforms, probably are spread through several months in the aftermath of the crisis. Thus, Mexico did not seem to suffer a Korea-type effect from its major local crisis.

[Insert Figures 5c and 5e here]

Finally, if all three parameters are allowed to change in Thailand, the break is dated in 1988, the official date of liberalization of the market. Thus, again we find that the date of liberalization led to a change in the behavior of the volatility of the market. The results show that the Thailandese market becomes unconditionally more volatile after liberalization, although conditionally less volatile, and less sensitive to the arrival of new information. Volatility, on the other hand, becomes more persistent. We find therefore different effects of the liberalization of the Thailandese market to what we found in the rest of the countries. The market became more volatile and more persistent, instead of less, but less affected by the arrival of news. Liberalization came hand in hand with a large increase in capital flows, especially from the US (Bekaert et al., 2002a). This increased flow of funds into the country's financial markets would lead to the described effects.

[Insert Figure 6c here]

4.3 Some Robustness Checks

Alternative tests for endogenous breaks in unconditional variance are available, although these tests are more nonconstructive in nature. The paper by Andreou and Ghysels (2002) reviews the most recently developed tests. We use two of those tests as robustness checks for our results on the endogenous breaks. Both tests are based on cumulative sums of either the squared returns or the absolute returns. As in traditional CUSUM tests, these tests rely on the fact that if there is a change in the behavior of the series, cumulative sums should depart at some point from what would be implied if the behavior over the full sample were uniform. The two tests that we apply are those in Kokoszka and Leipus (KL, 2000) and Inclán and Tiao (IT, 1996). Both can be applied to squared returns or to absolute returns, and are designed to test for the most likely location of a change in the unconditional variance of the series of returns. The asymptotic distribution of both tests is exactly the same, although the KL test is more general: The null under the IT test is that the series is i.i.d. and the alternative is that it has a level shift in variance. The KL test applies to a much wider range of series, including long memory, GARCH-type and some non-linear time series. Thus, it is expected to be more powerful in a time series context, where the i.i.d. assumption is highly dubious.[10]

The KL test for existence of a break in the variance of a return series r_t is constructed by first calculating the series of cumulative sums

$$U_T(k) = \left(1/\sqrt{T} \sum_{j=1}^{k} X_j - k/\left(T\sqrt{T}\right) \sum_{j=1}^{T} X_j \right) \tag{7}$$

where X_j is either the squared return r_j^2 or the absolute return $|r_j|$ at time j. The estimator of the date of the break is then taken to be the maximum of the values of the test:

$$k = \min \left\{ k : |U_T(k)| = \max_{1 \leq j \leq T} |U_T(j)| \right\} \tag{8}$$

The asymptotic distribution of the normalized test $KL = \sup \{|U_T(k)|\} / \widehat{\sigma}$, where $\widehat{\sigma}$ is some estimator of the long run variance, is a Kolmogorov-Smirnov type distribution, with critical values 1.22 and 1.36 for the 90% and 95% confidence levels respectively.[11]

The IT test is constructed with a different series of cumulative sums:

$$D_k = \left(\frac{\sum_{j=1}^{k} X_j}{\sum_{j=1}^{T} X_j} - k/T \right) \tag{9}$$

and again the date of the break is taken to be that of the maximum D_k, with the test statistic being rescaled as follows:

$$IT = \sqrt{T/2} \max_k D_k \tag{10}$$

The asymptotic distribution followed by this rescaled IT test is exactly the same as that of the normalized KL test.

Both tests can be applied sequentially in order to find multiple breaks. The sequential procedure detects the first break, and then applies the test again to the two subperiods identified by the first break. The date of the higher $\sup U_T$ or $\sup D_k$ of both subperiods is taken as the estimate of the second break, which in turn determines three subperiods and so on.

Table 6 reports the results of applying the KL and IT tests to our series of returns. We have carried out the test for both the squared and the absolute returns.[12] In Korea, for example, the sup-LR, the KL and IT tests locate the

[10] In fact, we have noticed that the IT test tends to give evidence of too many breaks (see Aggarwal et al., 1999 for an analysis of emerging markets volatility that uses this test). The results of the two tests can be seen to be in line with the $\sup -LR$, but the IT test is clearly biased towards finding breaks in time series.

[11] We use a Newey-West heteroskedasticity and autocorrelation-consistent estimator of the long run variance, with truncation lag determined by the rule $4(T/100)^{2/9}$.

[12] An AR(1) was first fitted to the returns, so that the tests are carried out on the residuals of that AR estimation.

break at the same date: August, 1997. Both tests yield a statistically significant break in squared returns, although the evidence for the absolute returns is a little weaker. It can be seen that in the Chilean case both test locate the break at a very similar date as the sup-LR test, in March 1983 (using absolute and squared returns).We find that the dates for the two breaks detected by the sup-LR test in Mexico (November 1981 and May 1988) are also detected by the IT test (with squared returns). We obtain the same dates of the break with the KL test although the test are not statistically significant for both dates. In the Brazilian stock market, we found no statistical break with sup-LR or KL tests. However, the IT test found a significant break in September 1984 (with squared returns). When we examine Argentina and Thailand we observe that the KL and IT tests detect the same date of the break (December, 1989 and February 1990 for Argentina and May, 1996 and August, 1996 for Thailand) whereas the sup-LR test detect a different date of the break (March, 1991 for Argentina and December, 1988 for Thailand). The second break detected in Argentina, Chile, Korea, Mexico and Thailand is not statistically significant according to the KL test. The IT test would, however, allow to reject the null of one single break in favor of the alternative of two breaks, but given the i.i.d. assumption underlying the test we believe that the evidence is not strong enough in favor of this second break: As said before, the IT test tends to find too many breaks in series with outliers (Aggarwal et al., 1999). In summary, the results of these CUSUM-type tests are in consonance with the results of the $\sup -LR$ test in the case of Brazil, Chile, Korea and Mexico.

[Insert Table 6 here]

5 Conclusions

In this paper we analyze whether the stock market volatility in some emerging countries has changed significantly over the last twenty five years and we try to identify the events that led to such changes. In a first step, and by means of a graphical analysis, we describe the time evolution of the stock market volatility. Afterwards, we locate endogenous structural breaks in the volatility behavior with alternative methodologies.

Our results, especially those in the last section, show different patterns of behavior of stock market volatility over time. In most of the cases, with the exception of Korea, affected by the Asian crisis, and Brazil, for which we did not find evidence of a break given its peculiar trending behavior, volatility in emerging markets tends to change due to local events of liberalization and opening of the (real or financial) markets (this is also the case of Brazil). Global events seem to impact all countries, but this impact is generally short lived and does not cause structural changes in the economies. Only Korea has experienced a structural change provoked by a global factor, although one might think that the Asian crisis was *especially local* to Korea.

We also find that the effect of liberalization processes is not homogeneous across countries. Whereas some of them see their stock markets stabilize (Mexico, Argentina, Brazil) and become less sensitive to news, some of them (Thailand) experience a clear increase in volatility following liberalization. Korea also experienced a noticeable increase in volatility, but its case is probably the most worrisome, given that also the sensibility of volatility to news increased markedly. Chile is a special case given that the significant change in behavior did not coincide with the official liberalization date, but took place long before, at the time of the stabilization plan and the beginning of the privatization process. In the case of Chile, volatility also decreased considerably at the time of the break.

Given the extreme importance of a smooth functioning of the stock market, efforts towards understanding the factors that make it more efficient, or the side consequences of its increased efficiency are likely to yield much fruit both for researchers and for people involved in economic policy. In the case of emerging markets, which are subject to added pressures and instability, a thorough analysis of the causes of changes in volatility can be also of use for policymakers in their efforts to bring their economies along a stable catch-up process, both in real and financial terms. Further research on this topic is therefore warranted.

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Table 1

Some basic statistics on the returns, 1976:01-2002:03

Returns are calculated as $12(\ln P_t - \ln P_{t-1})$, where P_t is the value of the stock index at month t.

SD: standard deviation.

SK: skewness coefficient.

κ : kurtosis coefficient.

ρ_1 : first order autocorrelation coefficient.

Q(4): Ljung-Box(4) statistic for autocorrelation of returns.

ARCH(4): ARCH-LM test with 4 lags. The value in the table is the asymptotic χ^2 test, using TR^2 of the auxiliary regression.

JB: Jarque-Bera normality test.

* and ** denote statistical significance at the 10% and 5% levels, respectively.

	Argentina	Brazil	Chile	Korea	Mexico	Thailand
Mean	0.1163	0.0144	0.1518	0.0696	0.0968	0.0241
SD	2.66	1.88	1.17	1.47	1.59	1.3
SK	0.11	-0.42**	0.33**	2.13**	-2.02**	-0.07
κ	8.24**	5.99**	4.92**	19.61**	12.67**	6.47**
ρ_1	0.022	0.021	0.153**	0.051	0.233**	0.082
Q(4)	0.98	3.14	17.3**	1.1	19**	12.8**
ARCH(4)	23.5**	8.1*	10.1**	48.1**	37.9**	44.3**
JB	360.8**	126.7**	54.1**	3857.6**	1442.4**	157.9**

Table 2
Asymptotic critical values of the sequential test $LR(l+1 \mid l)$

		l		
q	α	0	1	2
1	90%	8.02	9.56	10.45
	95%	9.63	11.14	12.16
	Argentina	26.95	6.07	- -
	Brazil	5.59	- -	- -
	Chile	14.32	1.51	- -
	Korea	12.73	7.54	- -
	Mexico	9.69	27	10.76
	Thailand	20.08	5.12	- -
3	90%	13.43	15.26	16.38
	95%	15.37	17.15	17.97
	Argentina	30.01	9.88	- -
	Brazil	10.39	- -	- -
	Chile	14.95	3.49	- -
	Korea	18.31	8.48	- -
	Mexico	15.88	21.81	13.32
	Thailand	24.33	10.35	- -

See Table II, Bai and Perron (1998).

Table 3

GARCH(1,1) model for the stock return volatility of some emerging countries, 1976:01-2002:03

$r_t = \beta_0 + \beta_1 r_{t-1} + u_{t-1} \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [Mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [Variance equation]

r_t is the rate of return at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The sample size is 315 months. * and ** denote statistical significance at the 10% and 5% levels, respectively. UV denotes the unconditional variance.

	Argentina	Brazil	Chile	Korea	Mexico	Thailand
β_0	0.0286	-0.0371	0.1072	0.1023	0.7140	0.0001
	(0.24)	(-0.40)	(2.07)	(1.52)	(0.86)	(0.001)
β_1	0.0617	0.0822	0.1888	0.0352	0.1728	0.0818
	(0.75)	(1.31)	(3.73)	(0.86)	(1.61)	(1.29)
ϖ_0	0.2363	0.0696	0.0251	0.1241	0.6279	0.0625
	(0.37)	(0.43)	(0.25)	(0.52)	(0.36)	(0.39)
α_1	0.7888	0.8758	0.8748	0.7653	0.5376	0.7818
	(3.39)	(15.51)	(5.78)	(7.08)	(0.45)	(7.35)
α_2	0.2052	0.1011	0.1187	0.1491	0.1824	0.1747
	(0.47)	(0.93)	(0.31)	(1.01)	(0.31)	(1.01)
UV	39.2313	3.0149	3.8486	1.4493	2.24	1.44

Table 4

GARCH(1,1) model with one break in the intercept, GARCH and ARCH effects for the stock return volatility of some emerging countries, 1976:01-2002:03

$r_t = \beta_0 + \beta_1 r_{t-1} + u_{t-1} \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [Mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [Variance equation]

r_t is the rate of return at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The sample size is 315 months. * and ** denote statistical significance at the 10% and 5% levels, respectively. UV denotes the unconditional variance.

	Argentina	Chile	Korea	Thailand
Period I				
β_0	-0.0961 (-0.44)	0.1985	0.0713 (0.98)	-0.0311 (-0.49)
β_1	0.0908 (0.97)	0.0932	0.0202 (0.53)	0.0831 (0.98)
ϖ_0	1.6421 (1.23)	0.2079	0.0764 (0.53)	0.1568 (0.73)
α_1	0.5475 (5.26)	0.9189	0.8502 (15.97)	0.4023 (3.81)
α_2	0.4039 (3.59)	0	0.0719 (1.01)	0.4157 (2.49)
UV	33.8231	2.5625	0.9823	0.8614
Break	1991:03	1983:02	1997:08	1988:12
Period II				
β_0	-0.0208 (-0.15)	0.1022	0.1395 (0.51)	0.0732 (0.74)
β_1	-0.0184 (-0.19)	0.2263	0.0527 (0.35)	0.0978 (1.26)
ϖ_0	0.2666 (2.33)	0.1952	3.4065 (5.27)	0.1125 (1.88)
α_1	0.8110 (14.43)	0.7026	0.0001 (0.01)	0.8519 (12.44)
α_2	0.0411 (0.71)	0.0609	0.2677 (1.61)	0.1026 (0.83)
UV	1.8026	0.8256	4.6517	2.4765

Table 5

GARCH(1,1) model with two breaks in the intercept, GARCH and ARCH effects for the stock return volatility in Mexico, 1976:01-2002:03

$r_t = \beta_0 + \beta_1 r_{t-1} + u_{t-1} \qquad u_t \longrightarrow iid(0, \sigma_t^2)$ [Mean equation]

$\sigma_t^2 = \varpi_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 u_{t-1}^2$ [Variance equation]

r_t is the rate of return at period t. σ_t^2 is the conditional variance of the stock return at period t. t-statistics use QML standard errors. The sample size is 315 months. * and ** denote statistical significance at the 10% and 5% levels, respectively. UV denotes the unconditional variance.

Period I	Period I	Period III	Period III
β_0	0.0210 (0.18)	0.0439 (0.18)	0.1409 (1.52)
β_1	0.3246 (2.31)	0.2204 (1.65)	0.1030 (1.18)
ϖ_0	0.6434 (0.94)	3.3737 (1.47)	1.2516 (1.60)
α_1	0.3204 (2.21)	0.1256 (0.79)	0.7E-07 (0.02)
α_2	0.1152 (1.33)	0.2295 (1.65)	0.078 (1.73)
UV	1.1397	5.2319	1.3575
Break	1981:11	1988:05	

Table 6. Alternative detection of the breaks

	Kokoszka and Leipus				Inclan and Tiao			
	$(r_t)^2$		$\|r_t\|$		$(r_t)^2$		$\|r_t\|$	
	Test	Break	Test	Break	Test	Break	Test	Break
Argentina								
One break	1.227*	1989:12	1.039	1990:02	3.774***	1989:12	2.122***	1990:02
Two breaks	0.787	1989:04	0.409	1989:03	1.981***	1989:04	4.698***	2001:10
Brazil								
One break	0.783	1984:09	0.570	1991:12	1.981***	1984:09	1.089	1991:12
Chile								
One break	1.389*	1983:04	0.837	1983:04	3.346***	1983:04	1.575**	1983:04
Two breaks	0.817	1978:02	0.493	1978:02	1.468**	1978:02	1.288*	2002:01
Korea								
One break	1.378*	1997:08	0.915	1997:07	4.013***	1997:08	1.809***	1997:07
Two breaks	0.889	1998:11	0.545	1998:11	1.725***	1998:11	3.328***	2002:01
Mexico								
One break	0.798	1988:04	0.525	1988:04	2.724***	1988:04	1.056	1988:04
Two breaks	0.866	1981:11	0.801	1981:11	2.691***	1981:11	3.263***	2002:01
Thailand								
One break	1.528**	1996:08	1.090	1996:05	4.381***	1996:08	2.246***	1996:05
Two breaks	0.912	1987:06	0.736	1986:05	2.403***	1987:06	3.592***	2002:01

Critical values: 1.22 (10%), 1.36 (5%) and 1.63 (1%).

Appendix 1. LIBERALIZATION PROCESS AND OTHER EVENTS

ARGENTINA

1976: Policymakers set out to dismantle government controls in prices, interest rates, international trade and capital flows (Suret and L´Her, 1997).

1977: Full liberalization of the banking system: Elimination of highly centralized banking arrangements to give incentives to domestic financial intermediation (Suret and L´Her, 1997).

1976: Financial reforms, including interest rate liberalization in 1978 (Rojas- Suarez and Weisbrod, 1992).

1978: Massive privatization initiative (Suret and L´Her, 1997).

1985: Austral Plan.

1989-90: Hyperinflation.

1989: Almost complete elimination of controls on prices, salaries, and foreign exchange transactions (Suret and L´Her, 1997).

1989: The newly-elected President Menem inmediately announced a privatization plan which led to sales in 1990 (Perotti et al. 2000).

1989: Official liberalization (Bekaert et al., 2002a).

1990: The Peso is pegged to US dollar.

1991: The tax on exports was eliminated. A major deregulation decree was issued. This ended a series of market-impeding rules and dissolved several regulatory bodies (Suret and L´Her, 1997).

1991: ADR introduction (1991:08) and country fund introducion (1991:10) (Bekaert et al., 2002a).

1992: October's massive deregulation program included the following provisions: The abolition of the 36 % capital gains tax on foreign investors, the elimination of fixed brokerage commissions and the introduction of foreign competition in the brokerage industry (Suret and L´Her, 1997).

1993: Increase in net US capital flows (1993:05)(Bekaert et al., 2002a).

1997: The Asian flu spills over to Argentina.

1999: The devaluation of the Brazilian real.

2001: Asia abandons the peg to the US dollar. Deposits are frozen and the country enters the most serious crises in the last decades.

BRAZIL

1976: The government began new efforts to stimulate interest in the market by creating the Securities Commission. Other measures included an attempt to attract foreign investors through special investment companies (Suret and L´Her, 1997).

1980: Interest rates were liberalized in November and a more relaxed price control policy was announced (Suret and L´Her, 1997).

1985: New legislation (Resolution No 1224) which enables foreign investment in the domestic capital markets through two new mechanisms: Foreign capital investment funds and managed portfolios of bonds and securities (Suret and L´Her, 1997).

1987: Country fund introduction (September) (Bekaert et al., 2002a).

1988: The Central Bank issued resolution No 1460, amending the previous regulations on debt / equity swaps. Accordingly, funds originating from conversions could be invested in the Brazilian securities market through foreign capital conversion funds (Suret and L´Her, 1997).

1988: One large privatization transaction (however, in 1989 and 1990 there were no sales) (Perotti et al., 2000).

1988: Increase in net US capital flows (July) (Bekaert et al., 2002a).

1989: Access of foreign investors to capital markets liberalized (Suret and L´Her, 1997).

1990: Anti-inflation plan, deposits confiscation, introduction of a new currency and presidential elections.

1990: Foreign investment in Brazilian equities became more favorable. The CVM plans to continue to liberalize rules for foreign investment (Suret and L´Her, 1997).

1991: Brazil's SEC announced new rules allowing foreign institutions to purchase shares listed on Brazilian exchanges directly (Suret and L´Her, 1997).

1991: Official liberalization date (May) (Bekaert et al., 2002a).

1992: A special tax on profit and dividend remittances abroad was eliminated and foreign investors were authorized to operate in future and option markets on interest rates and securities.

1992: ADR introduction (January) (Bekaert et al., 2002a).

1999: Brazilian crisis: The real is devalued.

CHILE

1970: Long tradition of privatization, extending back to the early 70's (Perotti et al. 2000).

1976: Allocative quotas and interest rate ceilings were abolished in 1976. Restrictions to capital flows were eliminated in 1976 (Faruqi, 1993).

1977: Deregulation of the country's financial system.

1978-82: Tablita Plan.

1979: International capital flows were freed and commercial banks were authorized to accept foreign deposits (Haggard, Lee, Maxfield, 1993).

1980: Establishment of a Securities Commission (Suret and L´Her, 1997).

1983: Second wave of privatization (Perotti et al. 2000).

1987: A law was enacted which provides the legal framework within which foreign investment funds may invest new money in the securities market (Suret and L´Her, 1997).

1988: Increase in net US capital flows (February) (Bekaert et al., 2002a).

1989: Country fund introduction (September) (Bekaert et al., 2002a).

1990: Official liberalization date (April) and ADR introduction (March) (Bekaert et al., 2002a).

KOREA

1981: The government allowed non- residents to begin indirect investment in equities (Suret and L´Her, 1997).

1984: Country fund introduction (August) (Bekaert et al., 2002a).

1985: For the first time, foreign investors were allowed to hold equity directly in Korean companies that sell convertible bonds overseas (Suret and L´Her, 1997).

1988: Official liberalization date (September) (Bekaert et al., 2002a).

1990: ADR introduction (November) (Bekaert et al., 2002a).

1991: Large trade deficits (Aggarwal et al. 1999).

1992: The capital market was being opened, as foreign investment was allowed up to 10% of the capital of listed companies (Kim and Singal, 1993 and De Santis and Imrohoroglu, 1997).

1993: Increase in net US capital flows (1993:04) (Bekaert et al., 2002a).

1997: Asian flu.

MEXICO

1981: Country fund introduction (1981:06) (Bekaert et al., 2002a).

1987-88: Anti-inflation plans.

1987: Financial sector was liberalized, measures included easier entry by domestic and foreign capital (Suret and L´Her, 1997).

1988: Privatization announcement started (Perotti et al. 2000).

1988: The financial sector was liberalized in 1988 (Faruqi, 1993).

1989: Regulations of foreign investment were modified to encourage investment by introducing automaticity and transparency and harmonizing the tax system. In some sectors, 100 % foreign ownership is allowed, 49 % and 30 % for brokerage houses and banks, respectively. Foreigners are now allowed to purchase securities in the Mexican stock market (Suret and L´Her, 1997).

1989: Official liberalization date (May) and ADR introduction (January) (Bekaert et al., 2002a).

1990: Price controls were relaxed (Suret and L´Her, 1997).

1994: Tequila crisis.

THAILAND

1985: Country fund introduction (July) (Bekaert et al., 2002a)..

1988: Increase in net US capital flows (August) and official liberalization date (December) (Bekaert et al., 2002a).

1989: Relaxation of foreign exchange dealings, switching the business from the central bank to commercial banks.

1990: Monetary arrangements liberalized; deposit interest rates (except savings deposit rate) have been completely freed; the foreign exchange regime and controls have also been further relaxed (Suret and L´Her, 1997).

1992: Commercial banks were permitted to undertake investment banking businesses. Adoption of the SEC act.

1993: In March, Thailand opened the door to foreign competition (Warner, 1994). Since early 1993, the ministry of finance had eased control on some finance and securities companies.

1997: Asian flu.

Figure 1a: ARGENTINA – SIMPLE TIME SERIES OF VARIANCE
Evolution of monthly returns: 1975–2001

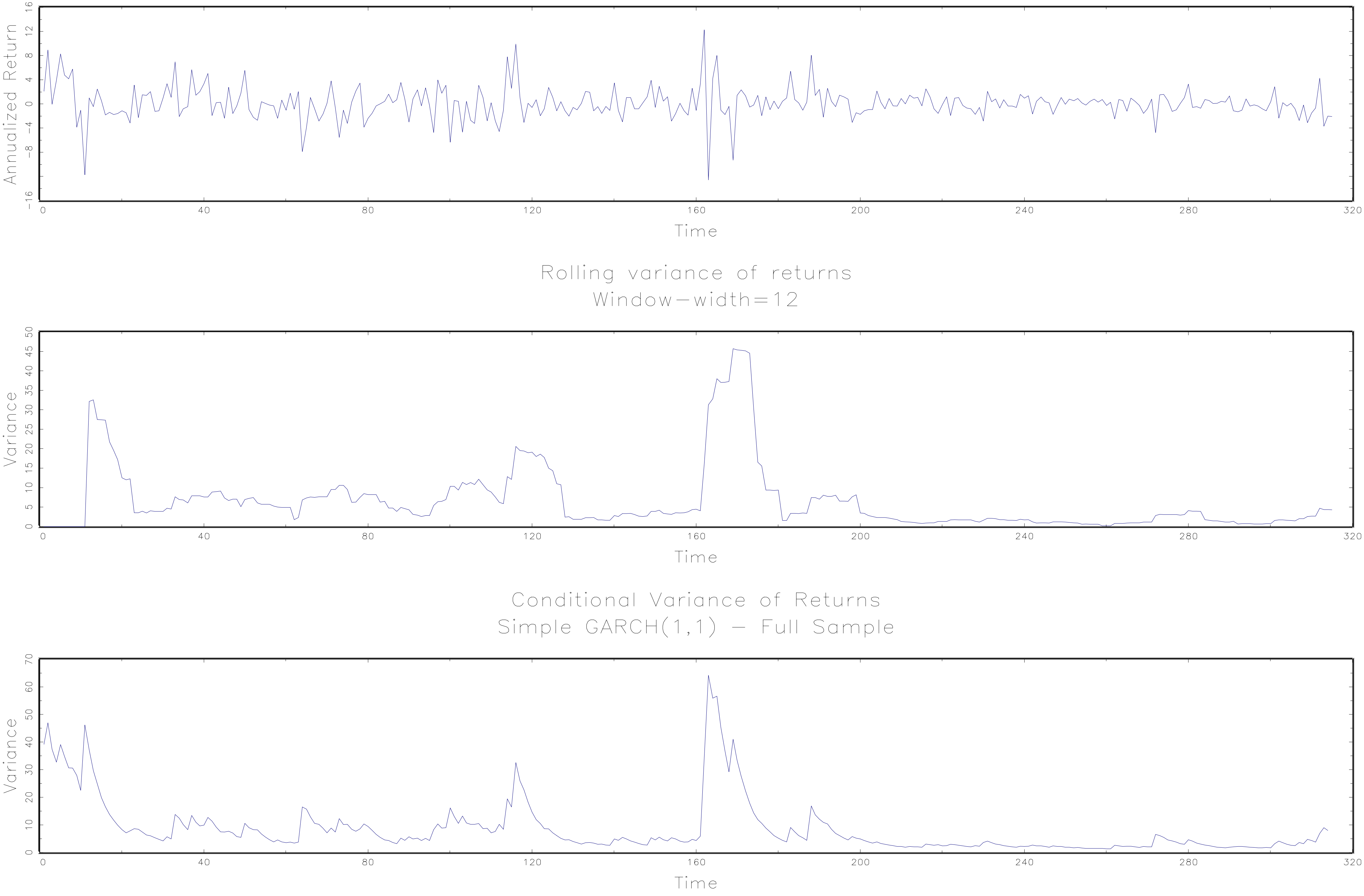


Figure 1c: ARGENTINA
BREAK IN ALL PARAMETERS OF GARCH EQUATION

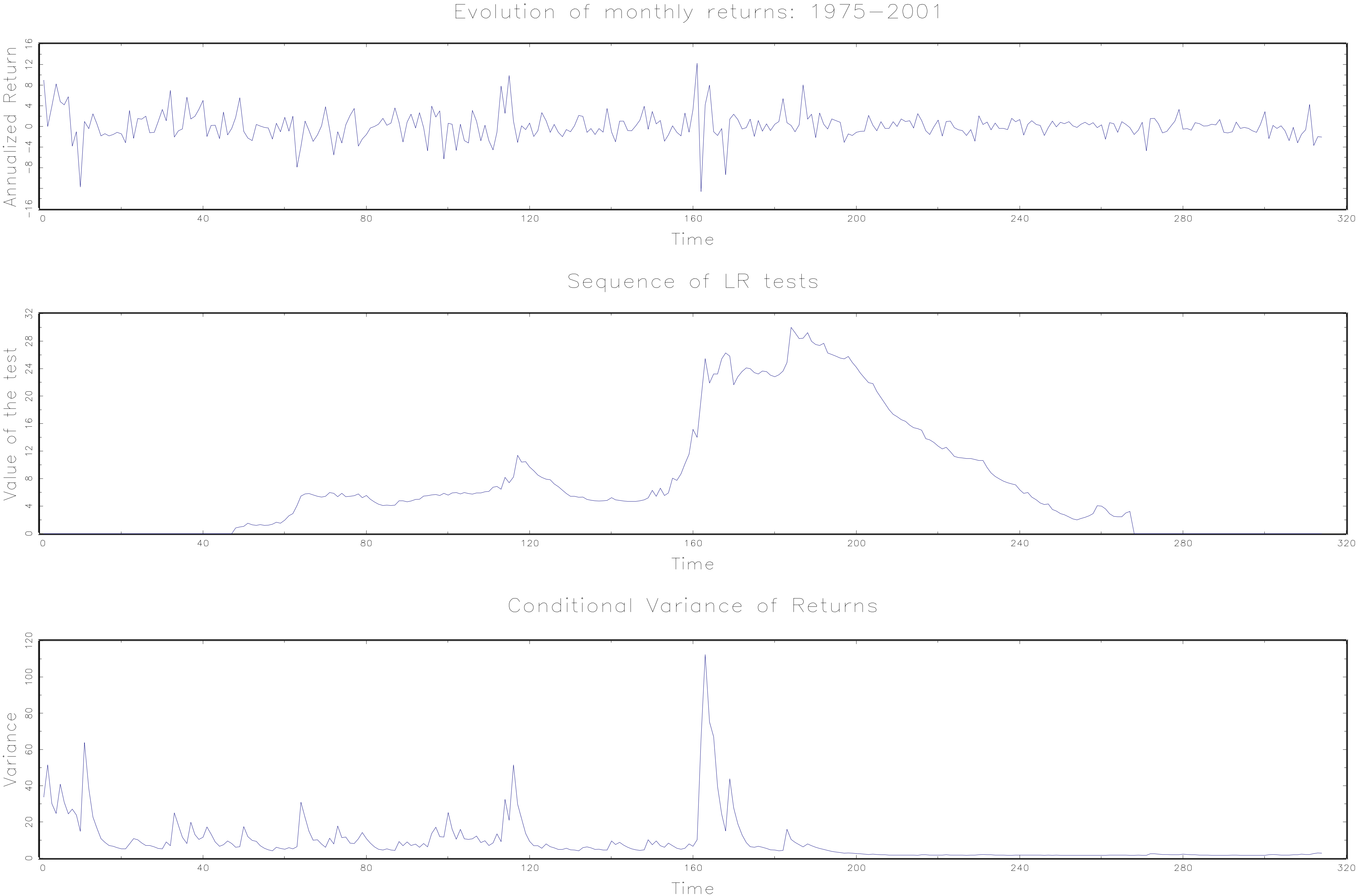
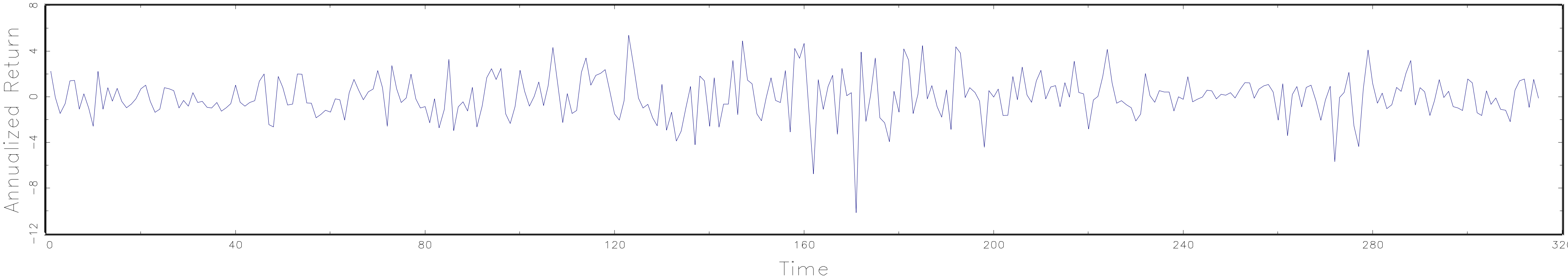


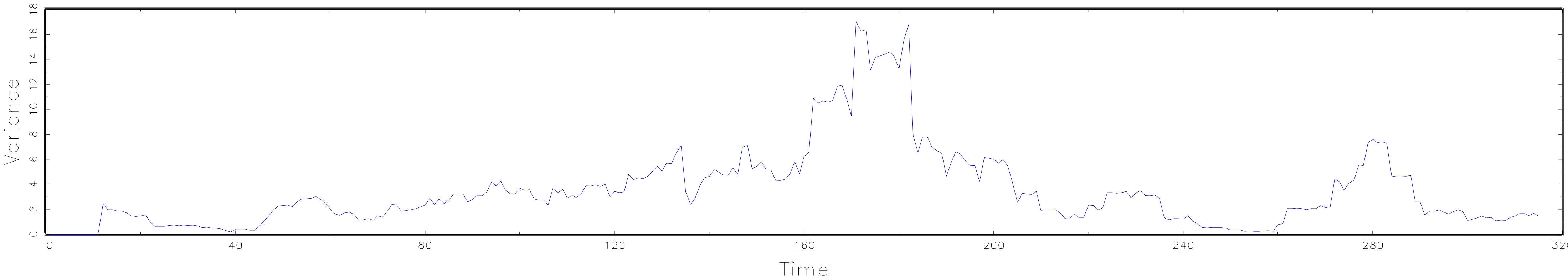
Figure 2a: BRAZIL – SIMPLE TIME SERIES OF VARIANCE

Evolution of monthly returns: 1975–2001



Rolling variance of returns

Window–width=12



Conditional Variance of Returns

Simple GARCH(1,1) – Full Sample

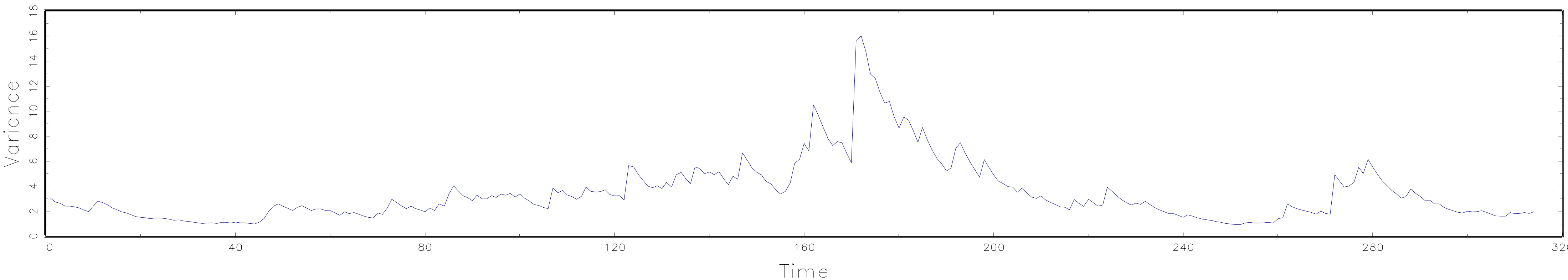


Figure 2c: BRAZIL
BREAK IN ALL PARAMETERS OF GARCH EQUATION

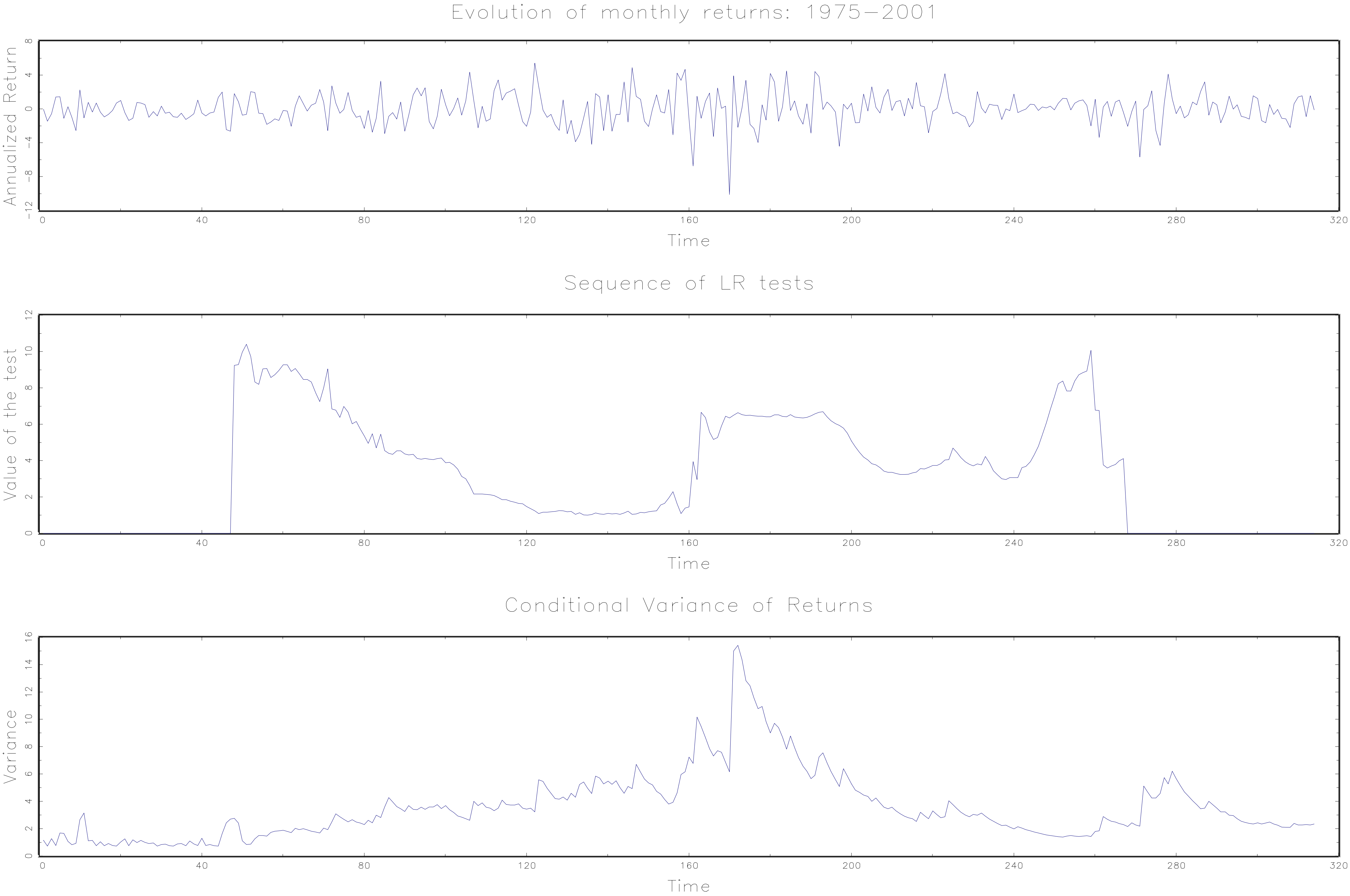
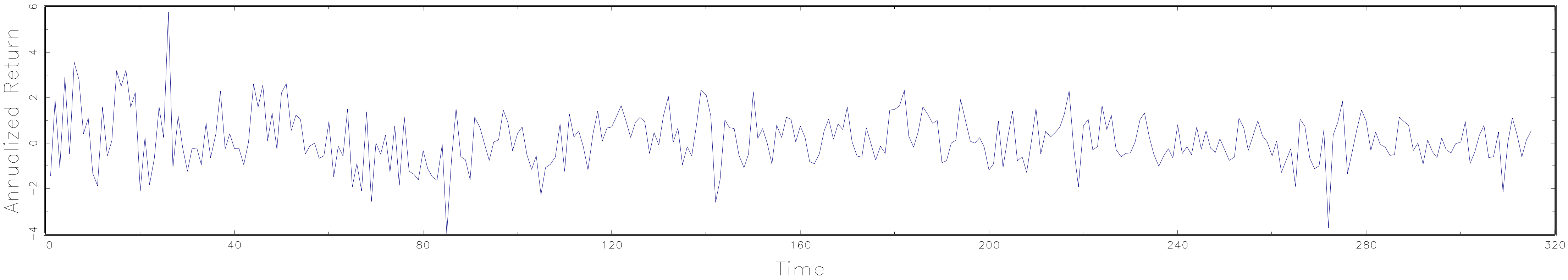


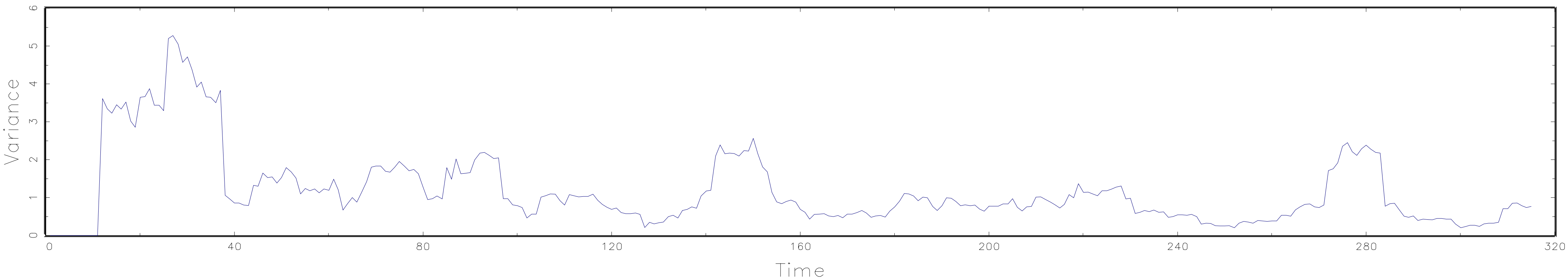
Figure 3a: CHILE – SIMPLE TIME SERIES OF VARIANCE

Evolution of monthly returns: 1975–2001



Rolling variance of returns

Window–width=12



Conditional Variance of Returns

Simple GARCH(1,1) – Full Sample

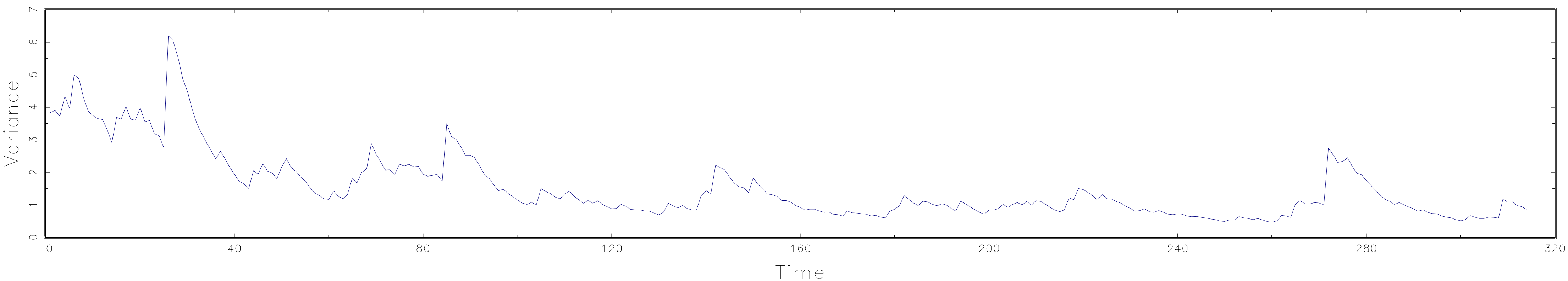


Figure 3c: CHILE

BREAK IN ALL PARAMETERS OF GARCH EQUATION

Evolution of monthly returns: 1975–2001

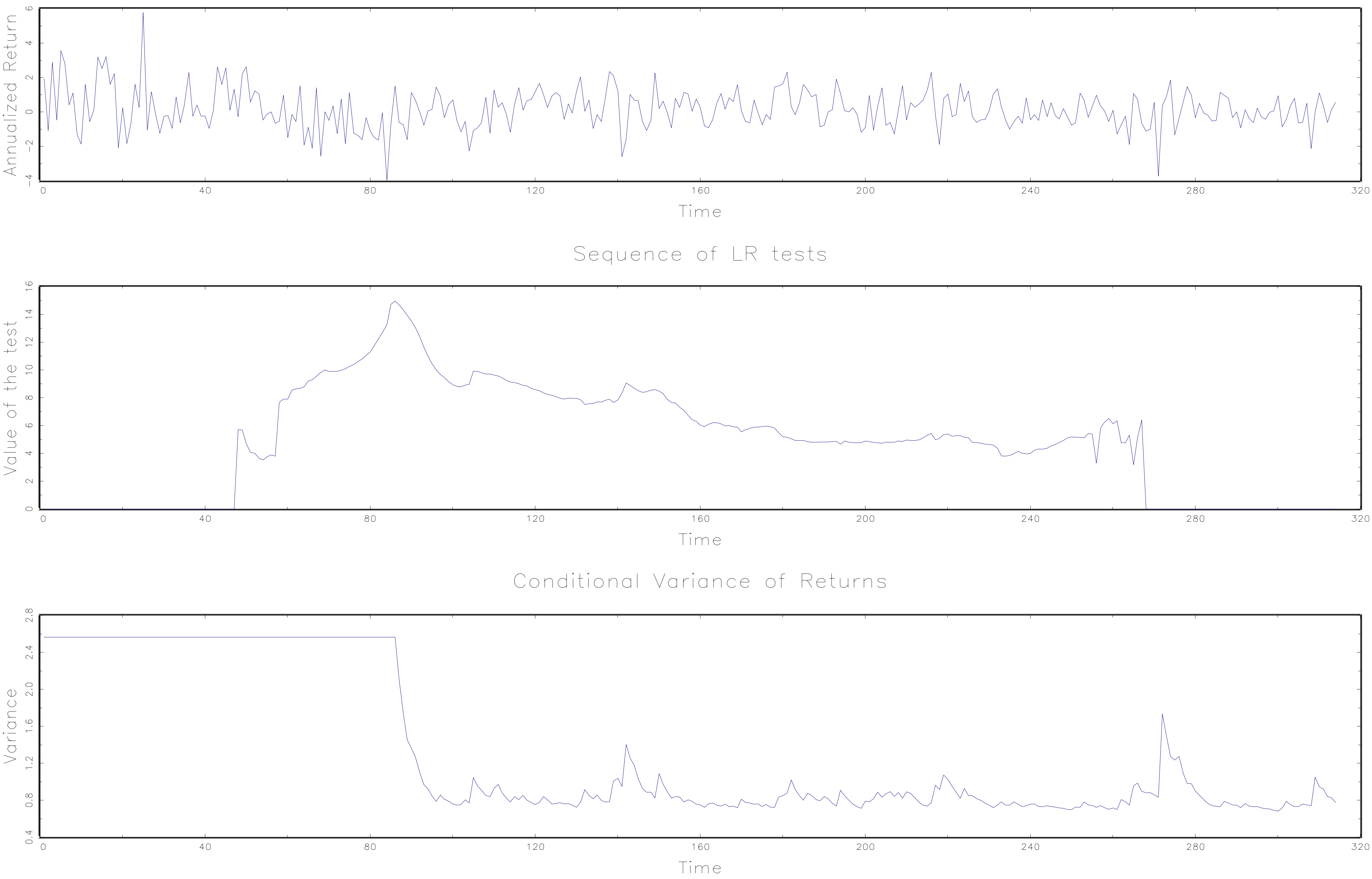
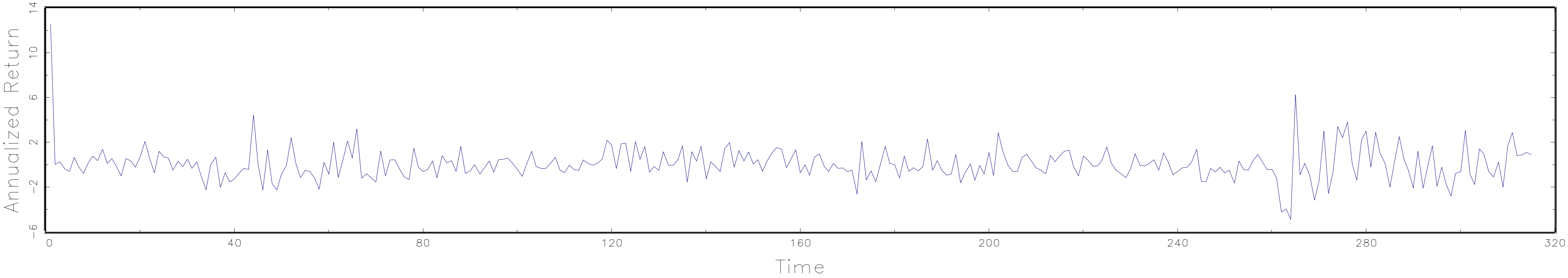


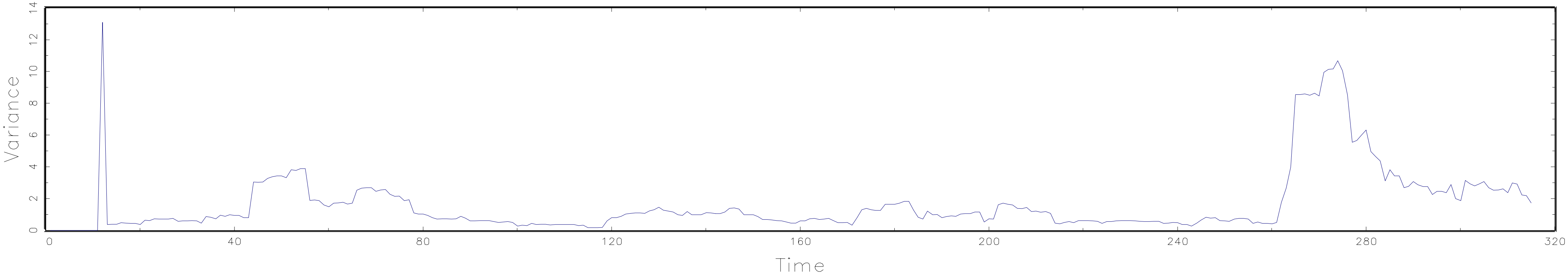
Figure 4a: KOREA – SIMPLE TIME SERIES OF VARIANCE

Evolution of monthly returns: 1975–2001



Rolling variance of returns

Window–width=12



Conditional Variance of Returns

Simple GARCH(1,1) – Full Sample

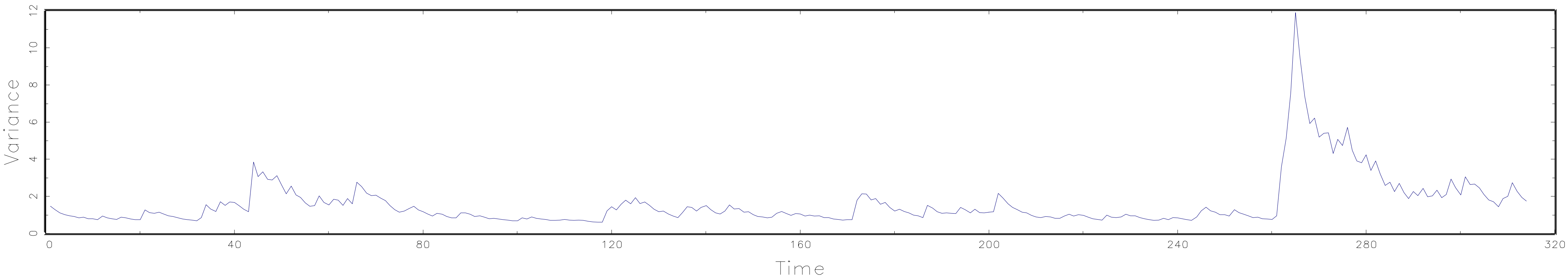


Figure 4c: KOREA
BREAK IN ALL PARAMETERS OF GARCH EQUATION
Evolution of monthly returns: 1975–2001

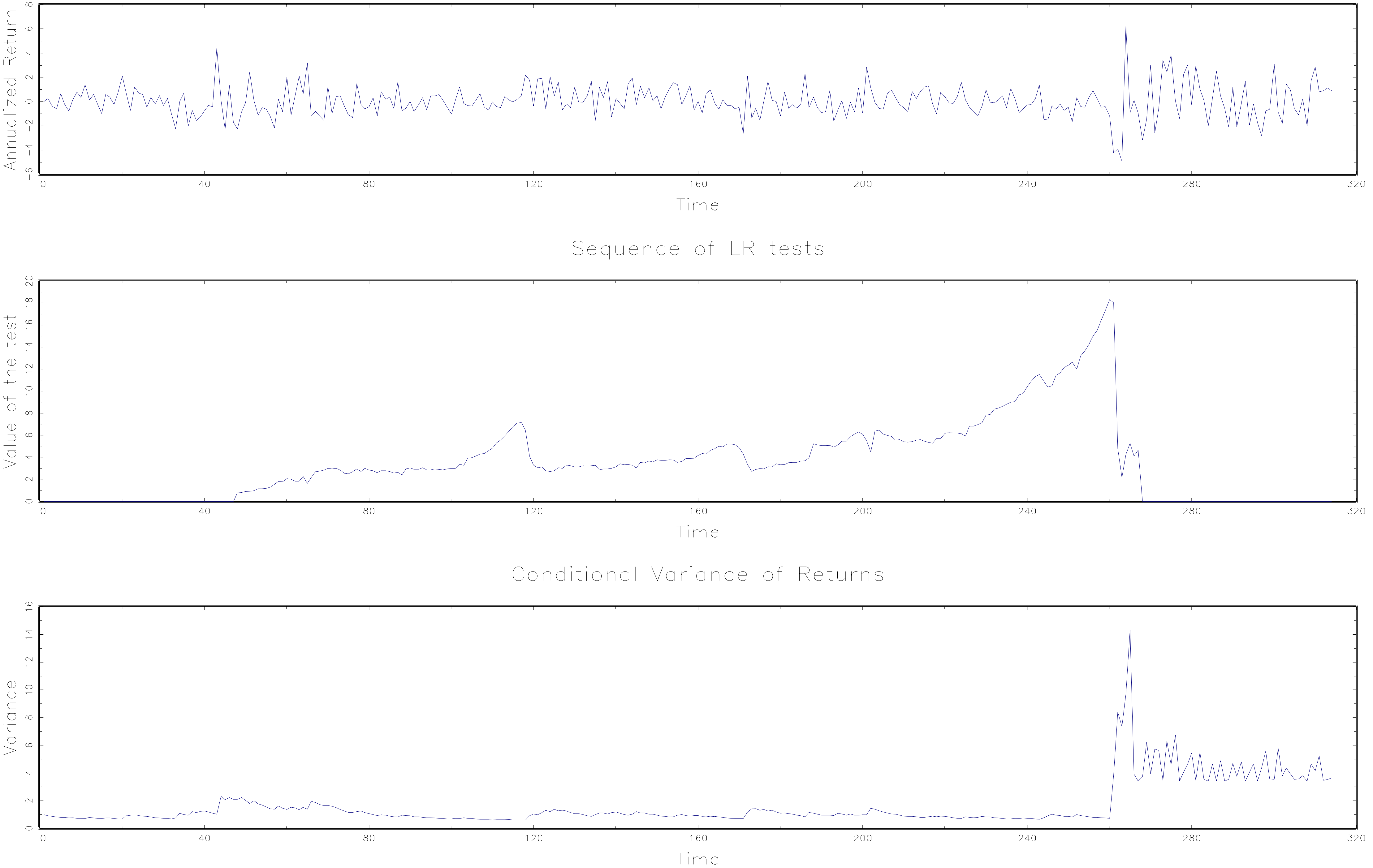


Figure 5a: MEXICO – SIMPLE TIME SERIES OF VARIANCE

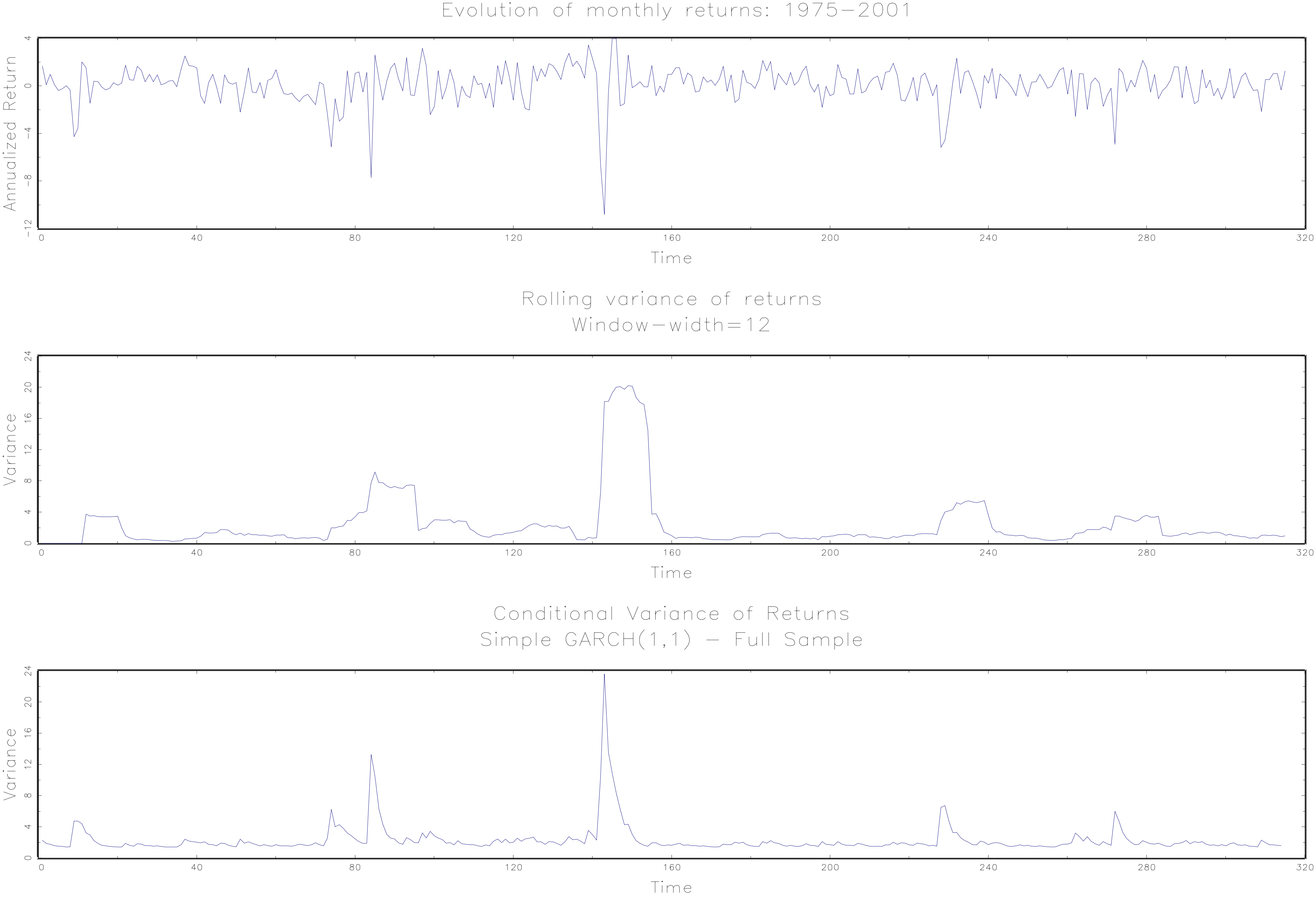


Figure 5c: MEXICO

BREAK IN ALL PARAMETERS OF GARCH EQUATION

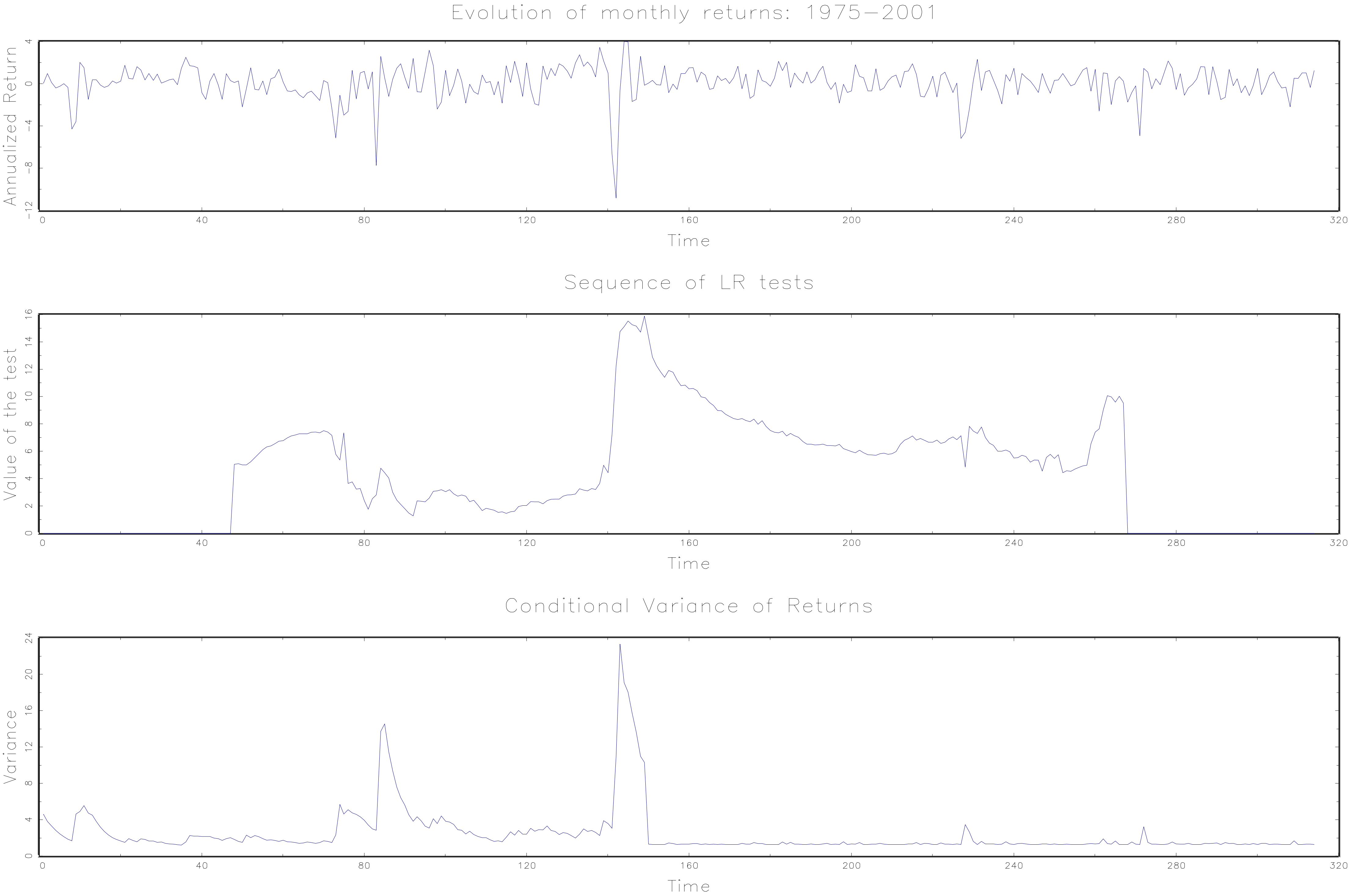


Figure 5e: MEXICO – TWO BREAKS IN ALL PARAMETERS OF GARCH EQUATION
(Conditional Variance used in Break)
Evolution of monthly returns: 1975–2001

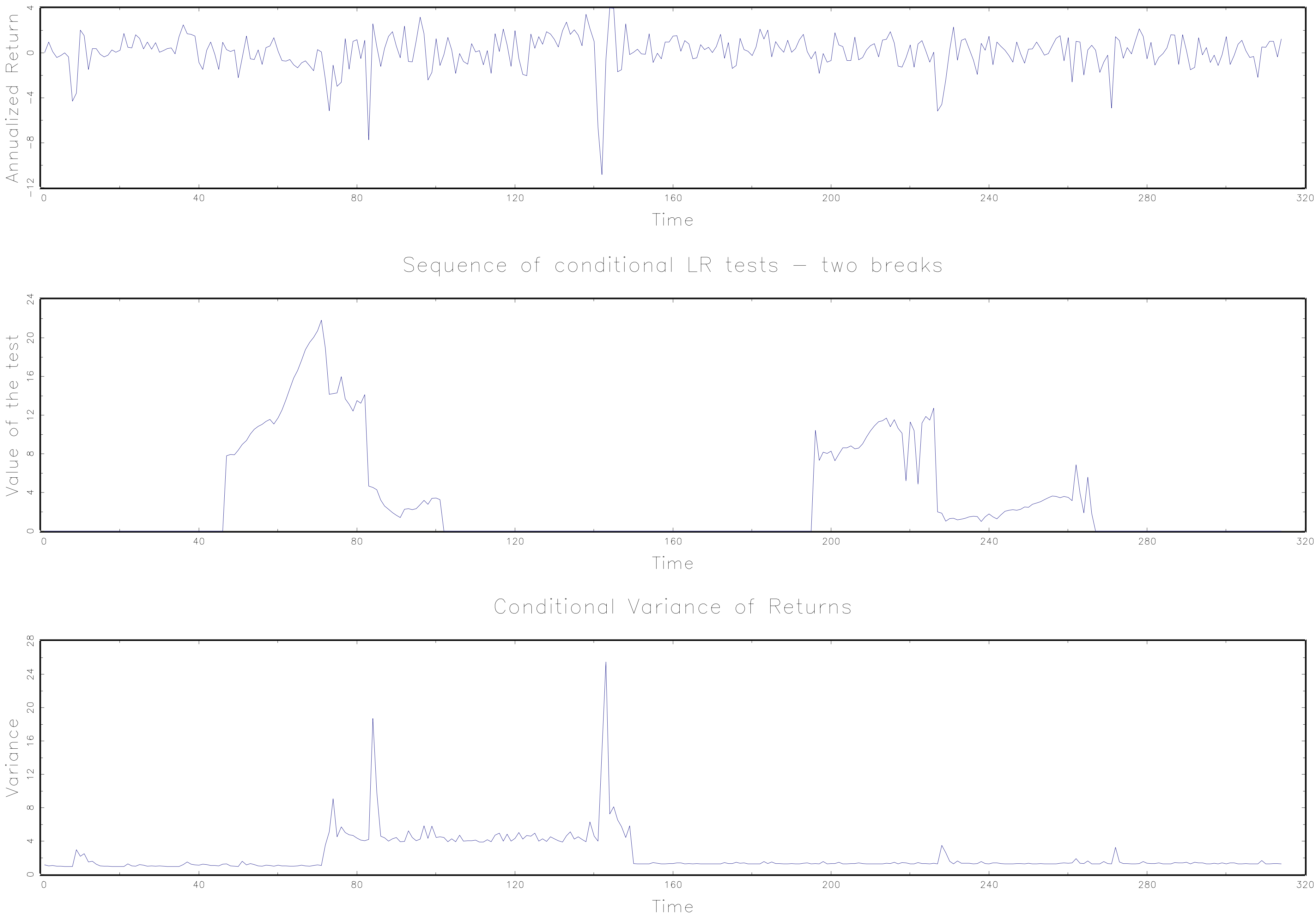


Figure 6a: THAILAND – SIMPLE TIME SERIES OF VARIANCE

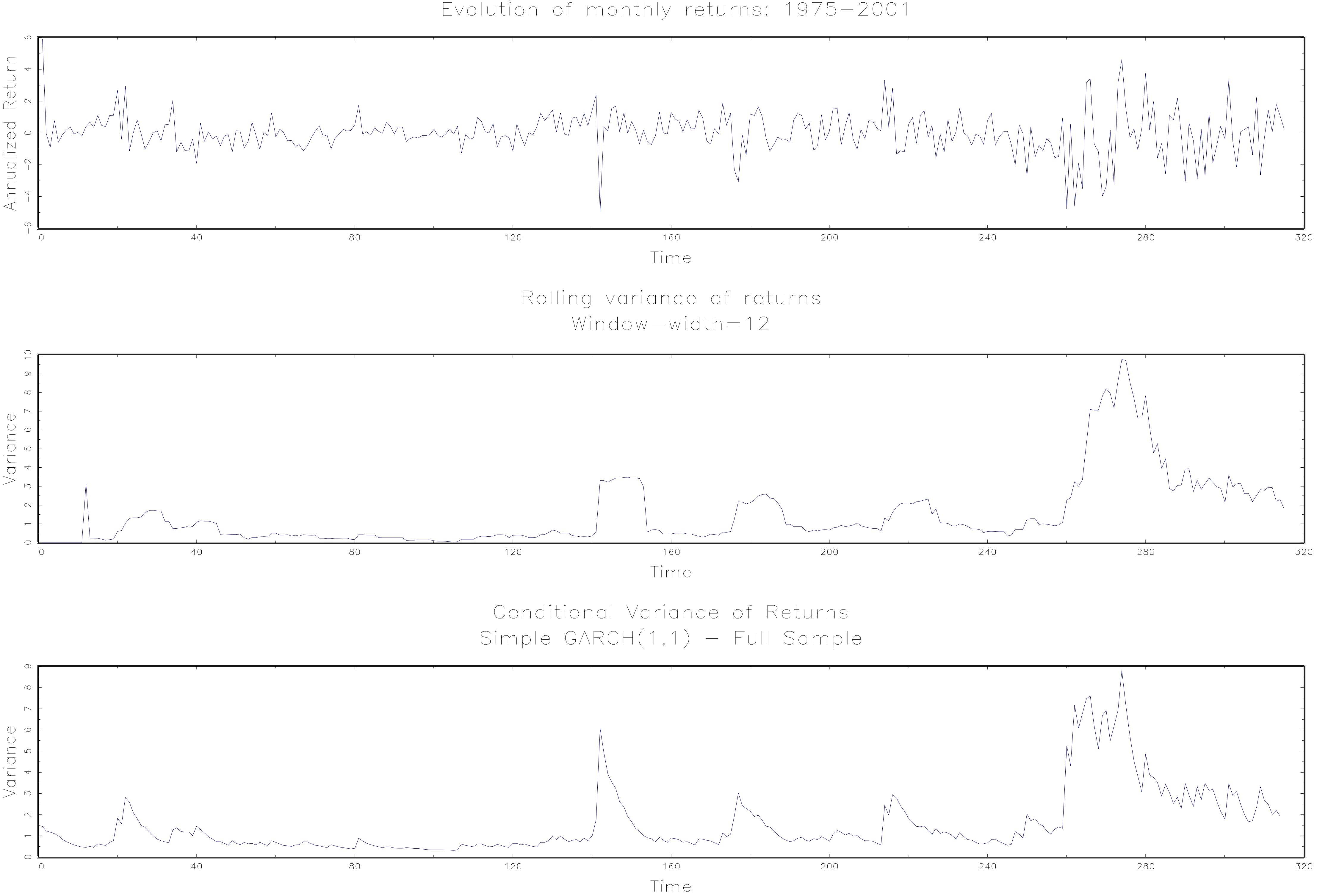


Figure 6c: THAILAND
BREAK IN ALL PARAMETERS OF GARCH EQUATION
Evolution of monthly returns: 1975–2001