Financial Liberalization and Emerging Stock Market Volatility

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Abstract

In this paper we test whether volatility in six emerging markets 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 of endogenous breakpoints detection that estimate the dates at which the behavior of the sotck market volatility changed. The analysis suggests that volatility has behaved in a different manner over the period.

JEL Classification: C32, G15, F36

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1 Introduction

During the late 1980s and early 1990s most Latin America and South-East Asian economies have experienced a number of economic reforms, financial liberalization and global integration processes.[1] For example, in Latin America

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[1] The reform blueprint has come to be known as the "Washington Consensus." A number of authors have argued that this reform process has failed, and that the Latin American countries have grown at slower rates and have become more unstable. For an analysis of the reforms see, for example, Edwards (1995). See Stiglitz (2002) for criticism of the reform process. Edwards (2003) assesses the validity of Stiglitz's critique.

deregulation and privatization were undertaken to reduce the importance of the government in the economy, and product markets were generally opened to greater international competition. In addition, domestic …nancial market were liberalized, with credit controls and lending restrictions removed, access to international …nancial markets improved and the permissible activities of domestic …nancial institutions expanded (see for example Glick et al. 2001). However, this process of …nancial liberalization and economic reform has been tempered by recent …nancial crisis (e.g., Mexico 1994-95, the Asian crisis of 1997-98, and the crises in Rusia, Brazil and othe Latin American economies in 1998-99).

The recent crises and …nancial instability ilustrate the risk of …nancial liberalization. Financial instability has been at the center of recent discussions on economic performance in Latin America. While some authors have concentrated on currency crises, others have gone beyond exchange rates and have dealt with more broadly de…ned …nancial markets, investigating the behavior of interest rates and stock returns during the post market-reform period. For example, Fischer (2002) has analyzed the implications of the Latin American currency crises for the future of the international monetary system. Eichengreen (2003), De Gregorio et al. (2000), and Edwards (1999) have investigated the role played by capital mobility in Latin America during the …nancial crises of the 1990s. Goldstein (2003) has looked more speci…cally at the forces behind the …nancial turmoil in Brazil during 2002. An important question, and one that is at the center of recent criticisms of the reform process and the Washington Consensus, is whether stock market have shown an increase in volatility -i.e. increased instability- in the post-…nancial liberalization era.

In this paper we focus on one aspect of the stock market evolution, and analyze whether stock market volatility has changed signi…cantly over the period 1976-2002 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 signi…cant 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 are particularly interested in adressing the following questions:

² Has stock market volatility changed throgh time in emerging economies? Has it changed across countries?

² How do stock market volatility mani…est across the emerging countries? Do emerging stock markets experience a higher level of volatility? Or do emerging stock markets experience a higher persistence?

² It is possible to …nd a relationship between changes in emerging stock market volatility and …nancial liberalization?

² From an methodological point of view, structural changes in emerging stock markets, would be explained by high returns in stock market?

We start our analysis with a …rst look at the data: we estimate some descriptive statistics of the stock market volatility and we present a simple graphical analysis of the evolaution of the rolling measure of stock return volatility.

The rolling variances give evidence of the existence of time structure of a typical ARCH-type, that identi…es 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 unspeci…ed) number of structural breaks, following the procedures suggested by Bai and Perron (1998, 2003a,b) and already successfully applied by Bekaert et al. (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 relationship between …nancial liberalization and stock market volatility. In Section 3, we present a …rst look at the stock market volatility behavior in some emerging markets. Section 4 analyzes changes in stock markets volatility in some emerging countries using a battery of methodologies. Finally, in Section 5we present a brief summary of the results and some concluding remarks.

2 Financial Liberalization and Stock Market Volatility

Since the mid 1980s most of the emerging countries were involved in …nancial liberalization processes. According to …nance theory, stock market volatility could increase or decrease when markets are opened (see for example Bekaert and Harvey 1997, 2000, 2002, 2003). On the one hand, markets may become informationally more e¢cient leading to higher volatility as prices quickly react to relevant information; also, 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. After liberalization, the gradual development and diversi…cation of the markets could lead to lower volatility.

Considerable research has focused on stock market liberalization and stock market volatility (e.g., Bekaert and Harvey 1997, Bekaert et al. 2002a, De Santis and Imrohoroglu 1997, Huang and Yang 1999, Kim and Singal 2000, Aggarwal et al. 1999, Kaminsky and Schmuckler 2003 and Edwards at al. 2003 among others) and the empirical evidence is mixed. For example, De Santis and Imrohoroglu (1997) study the behavior of volatility in some emerging countries and the e¤ect of liberalization of …nancial markets. They …nd signi…cant evidence for time-varying volatility and di¤erent e¤ects 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.[2]

[2] 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.

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 …nancial markets, both in developed countries, some of which did not fully liberalize capital ‡ows 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 …nancial market development. Thus, these countries provide with a natural experiment on the e¤ects 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 …nancial side has advanced quite substantially in the last years, mostly pro…ting from analyses based on emerging markets. Given the recent history of …nancial crises in developing economies, that have sometimes spilled over to developed economies and had caused real e¤ects in both developing and developed, a deep understanding of the factors that a¤ect …nancial markets becomes of extreme priority.

In this Section we use monthly data on stock returns for Argentina, Brazil, Chile, South Korea, Mexico and Thailand. These data correspond to the S&P/IFCG Emerging Market Indexes of Standard & Poor's, formerly calculated by the IFC.[3] The series run from 1976:01 to 2002:03, thus yielding a total of 315.[4]

We …rst estimate some descriptive statistics of the emerging stock market volatility and the we move to a simple graphical analysis. Table 1 reports basic univariate statistics for the (annualized) stock returns of our six markets. 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 coe¢ cients of skewness and kurtosis reveal nonnormality in all countries, a result con…rmed by the Jarque-Bera normality test. The Ljung-Box Q-statistics along with the autocorrelations indicate signi…cant autocorrelations in Chile, Mexico and Thailand. The LM-ARCH(4) univariate tests reveal ARCH e¤ects 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.

[3] These indexes, formerly calculated by the IFC, are dollar denominated price indexes of the stock markets in each country. We use the Global index and not the Investable, which is a narrower index that is only available from the 1990s on. The S&P/IFC Global index represents the performance of the most active stocks in each market analyzed and attempts to be the broadest possible indicator of market movements, corresponding to at least 75% of total capitalization. For further information on these widely used indexes, consult www.standardandpoors.com.

[4] Data availability and comparability also dictated the …nal set of countries analyzed. Some local indexes, such as Brazil's Bovespa and Chile's IGPA, were available for longer periods, but we opted for using a uniformly calculated index to make comparison across countries more meaningful and not subject to the di¤erent methodologies used by the countries. Still, one would ideally use as long a series as possible.

[Insert Table 1 here]

The dynamics of stock market volatility can be seen in Figures 1a-6a for each country. These figures show the evolution of the stock returns in some emerging economies during the sample period, a nonparametric measure of return volatility (12-month rolling variance) together with the forecasts of the conditional variance - the series of estimated σ_t^2 derived from the variance equation - coming from the GARCH model.[5]

This annualized rolling variance is calculated as follows:

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

where r_t is the return of the stock market index over period t and μ_{12} is the sample mean over the 12 month window.[6]

This nonparametric variance gives a first idea of the evolution of the conditional variance of the different stock markets. The volatility 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).

[Insert Figures 1a-6a here]

The rolling variance for Argentina shows the evolution of the volatility of Argentine returns. There have been three important negative returns in the Argentine stock market, 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 hyperinflation.[7] 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.

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 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

[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.

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

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

sample. During the period 1989-1991 several anti-in‡ation plans were adopted and con…scation of …nancial 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 1980s.

The rolling variance for Chile shows that the average level of volatility seems to have gone through three di¤erent periods. First, we encounter a period of high volatility during 1976-1979. After 1979 - during the Tablita Plan - and coinciding with the …rst opening of the market to international capital ‡ows, average variance drops signi…cantly. Then a period of relatively low variance follows. Finally, after 1995 the variance seems to fall again.

In the case of the Korean stock market returns, 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 ‡u disrupted Asian …nancial markets. The variance, however, seems to be returning, in the last dates of the sample, to pre-crisis levels.

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-in‡ation 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.

Thailand shows a most interesting evolution. The …rst, of extremely low variance and where no signi…cant "bad news" are present, runs from the beginning of the sample until around 1987-88. In this period, that coincides with the o¢cial date of …nancial market liberalization in Thailand a big negative return provokes 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 ‡uctuations.

4 Structural Breaks in Emerging Stock Market Volatility

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 …nancial liberalization and economic policy decisions.

In this paper, we follow a similar approach to Aggarwal et al. (1999) and 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. GARCH 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 and Cuñado et al. (2004) in the Spanish case.[8]

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

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

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 $\sigma_t^2 = \hat{\varpi}_0 + \hat{\alpha}_1\sigma_{t-1}^2 + \hat{\alpha}_2 u_{t-1}^2$, starting with $u_0 = 0$ and $\sigma_0^2 = \hat{\varpi}_0/(1 - \hat{\alpha}_1 - \hat{\alpha}_2)$.

In order to analyze whether the stock market volatility has changed throgh time in emerging economies we have proposed some alternative GARCH(1,1) specifications where we allow for breaks in the parameters in the variance equation. We explain in the next subsection the methodology followed to detect the endogenous breaks in the variance process. Finally, we 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).

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 (e.g., Banerjee et al. 1992, Ghysels et al. 1997, Bai et al. 1998). The issue of estimation of the number and location of multiple endogenous structural breaks is also being an active field of research (e.g., Andrews et al. 1996, García and Perron 1996, Bai 1997, 1999, Lumsdaine and Papell 1997 or Bai and Perron 1998, 2003a,b).

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. We use the general framework in Bai and Perron

[8] See Bollerslev et al. (1992) for an exhaustive review of this literature.

(1998, 2003a,b) and their procedure of sequentially locating the breaks with its associated critical values.

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,

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

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 $\mathbf{t}^* = \{\mathbf{t}, \tau\}$, 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 supLR 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 supLR test, the date of the new breakpoint $\widehat{\tau}$ is

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

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 $\hat{t}$. The values of the parameters before and after the break correspond to the estimates in $\hat{\theta}(t^*)$. The different versions of this statistic (Bai et al. 1998, Bai and Perron, 1998, 2003a,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 $LR(l + 1 | l)$ 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 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 $t = \{t_1, t_2, ...t_l\}$ 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.[9] That is, we start by locating the first breakpoint in $T^* = \{0.15T, 0.85T\}$ and then every time we locate a new breakpoint, we exclude from T^* the 15% observations to both sides of the last breakpoint estimated.[10]

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 comment on the six countries separately.[11] The main results can be summarized as follows. First, we detect for most of the emerging countries that

[9] 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.

[10] Notice that the procedure outlined above could be considered a sequential location of breakpoints. That is, given that $t = \{t_1, t_2, ...t_l\}$ 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 2003a,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.

[11] 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

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 ‡u 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 signi…cant, 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 a¤ected in a structural manner by the Asian ‡u, 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 signi…cantly. Notice that this result is in contrast with usual …ndings 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.

Most of the countries went through a liberalization process during the 1980s.[12] 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 signi…cant 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 ‡u, all markets seemed to be momentarily a¤ected, but only Korea truly showed a lasting e¤ect. The rest of the countries have been mostly a¤ected, in a structural manner, by their own particular economic events, whereas external events have tended to create only short lived instability.[13]

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

[Insert Tables 3-5 here]

Results for Argentina can be seen in Table 4. Argentina presents one single signi…cant 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 - when all parameters are allowed to change- con…rm the fact that the volatility of the Argentine stock market was substantially reduced around 1991. 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 a¤ected by the coming of new information: We have already found evidence of this e¤ect in the nonparametric variance in Figure 1, where it was clear that large (negative) returns had a substantial e¤ect 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

including only the …tted variance for the …nal model chosen for each country. All other …gures and sequences of LR tests are of course available upon request.

[12] For a detailed chronology of …nancial liberalization in emerging countries see http://www.duke.edu/~charvey/Country_risk/couindex.htm.

[13] Aggarwal et al. (1999) found a similar result.

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[14] and to start presenting signs of maturity, such as the reduced effect of news.

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 2a that the simple GARCH model is already accounting quite well for the complete evolution of the variance.

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 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 4 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.

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

[14] 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.

also changes more abruptly (lower persistence, see Figure 4a). 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.

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 is 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.

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.

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).[15] 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.[16]

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

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

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:

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

The asymptotic distribution of the normalized test $KL = \sup\{|U_T(k)|\}/\hat{\sigma}$, where $\hat{\sigma}$ 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.[17]

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:

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

[15] These two test are used bu Cuñado et al. (2004) to test structural breaks in Spanish stock market volatility.

[16] 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 with GARCH effects.

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

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 supU_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.[18] In Korea, for example, the sup-LR, the KL and IT tests locate the 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 tests 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

During the late 1980s and early 1990s the vast majority of the Latin America countries embarked on ambitious market-oriented reforms and financial liberalization. An important question, and one that is at the center of recent criticisms of the reform process and the Washington Consensus,is whether stock market have shown an increase in volatility -i.e. increased instability- in the

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

post-financial liberalization era. 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 methodology.

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, although we cannot detect its type of change with our methodology). 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 coe¢cient.

κ : kurtosis coe¢cient.

ρ_1 : …rst order autocorrelation coe¢cient.

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 signi…cance 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

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

$r_t = \beta_0 + \beta_1 r_{t-1} + u_{t-1} \quad u_t \sim iid(0, \sigma_t^2)$ [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

$r_t = \beta_0 + \beta_1 r_{t-1} + u_{t-1} \quad u_t \sim iid(0, \sigma_t^2)$ [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	0.0439	0.1409
	(0.18)	(0.18)	(1.52)
β_1	0.3246	0.2204	0.1030
	(2.31)	(1.65)	(1.18)
ϖ_0	0.6434	3.3737	1.2516
	(0.94)	(1.47)	(1.60)
α_1	0.3204	0.1256	0.7E-07
	(2.21)	(0.79)	(0.02)
α_2	0.1152	0.2295	0.078
	(1.33)	(1.65)	(1.73)
UV	1.1397	5.2319	1.3575
Break	1981:11	1988:05	

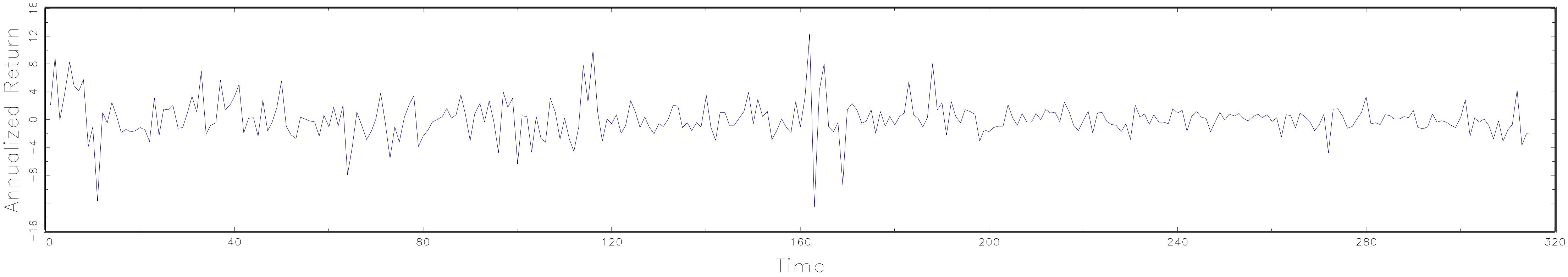
Table 6. Alternative breaks

	Kokoszka and Leipus				Inclan and Tiao			
	$(r_t)^2$		$\lvert r_t \rvert$		$(r_t)^2$		$\lvert r_t \rvert$	
	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%).

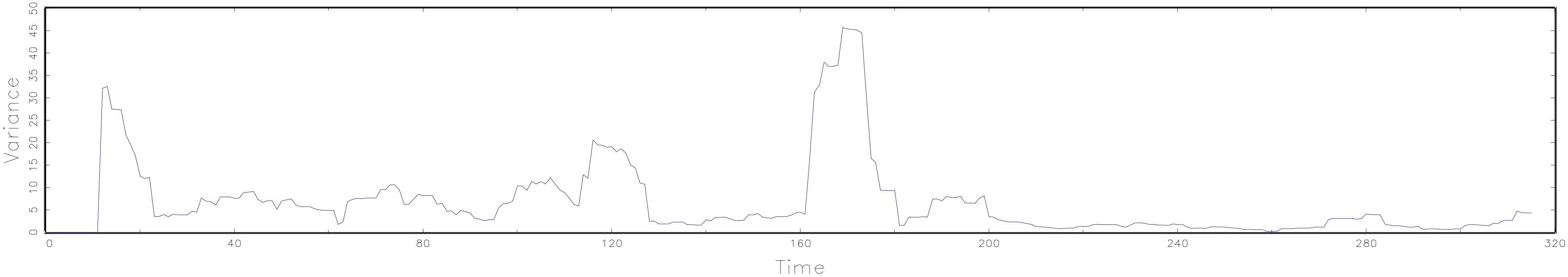
Figure 1a: ARGENTINA – SIMPLE TIME SERIES OF VARIANCE

Evolution of monthly returns: 1975–2001



Rolling variance of returns

Window–width=12



Conditional Variance of Returns

Simple GARCH(1,1) – Full Sample

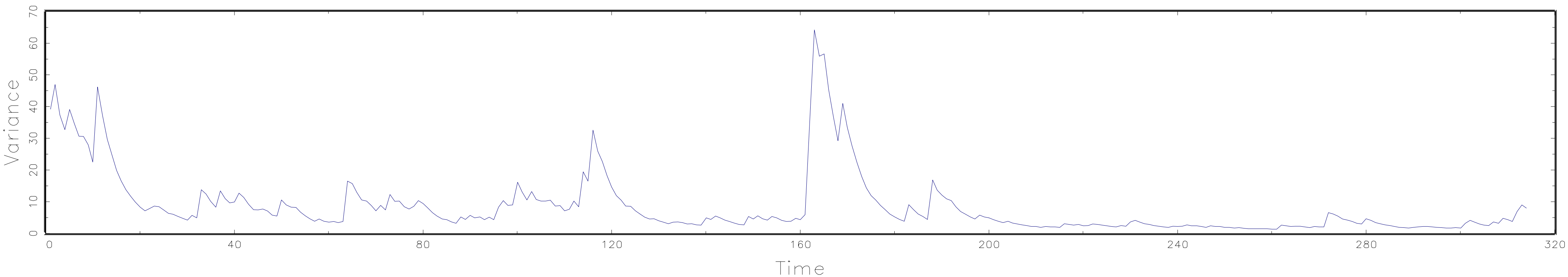


Figure 2a: BRAZIL – SIMPLE TIME SERIES OF VARIANCE

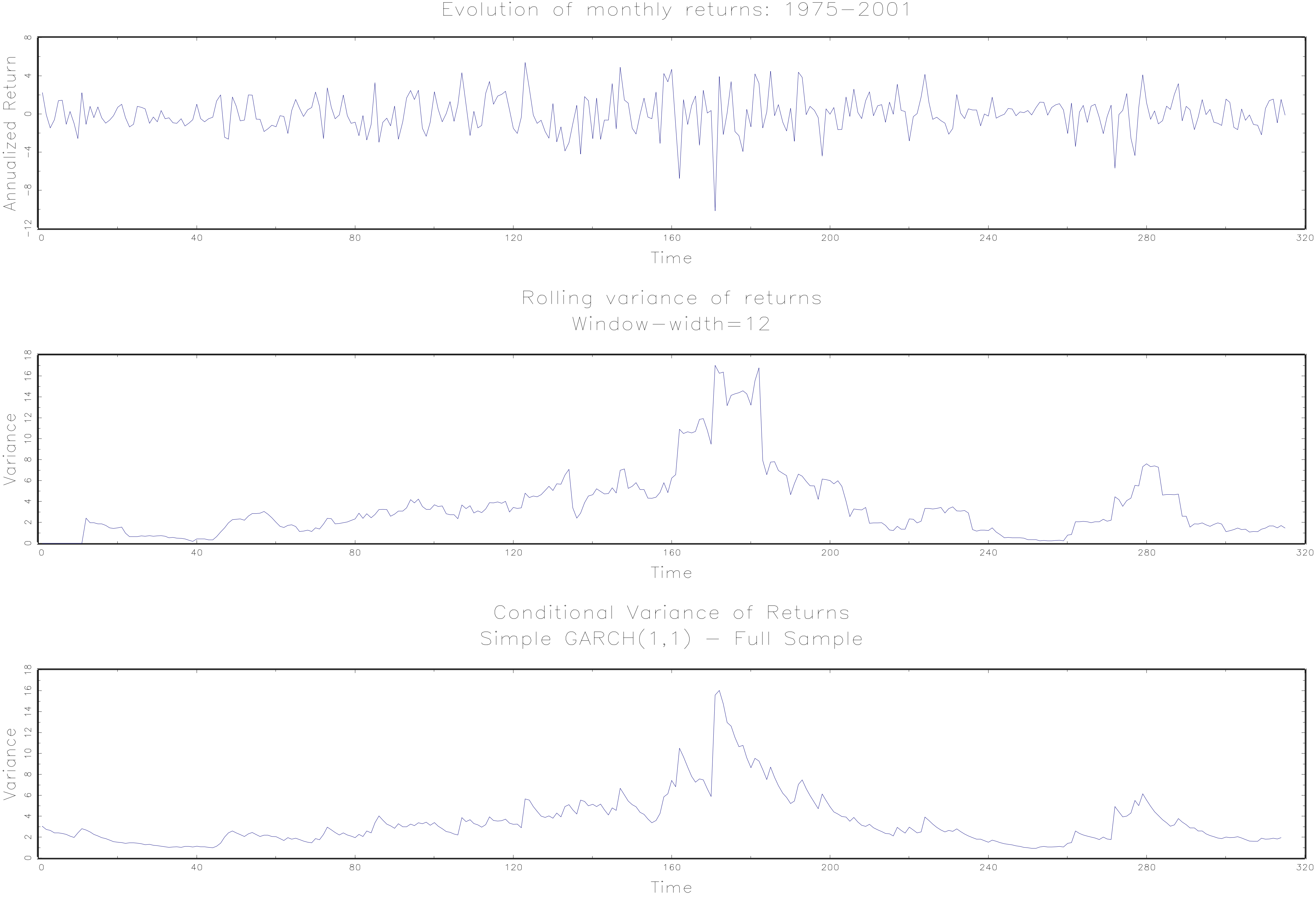
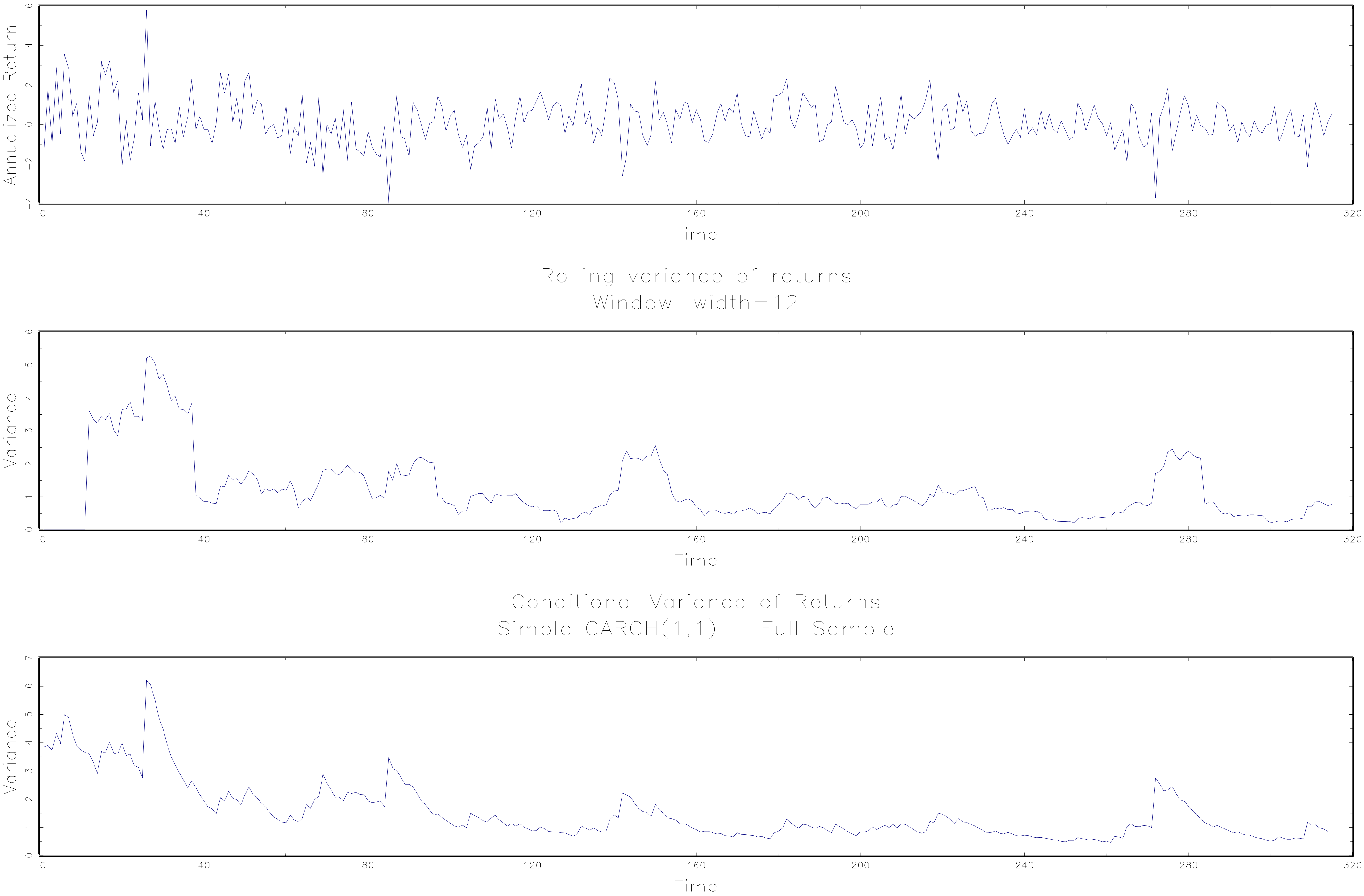


Figure 3a: CHILE – SIMPLE TIME SERIES OF VARIANCE
Evolution of monthly returns: 1975–2001



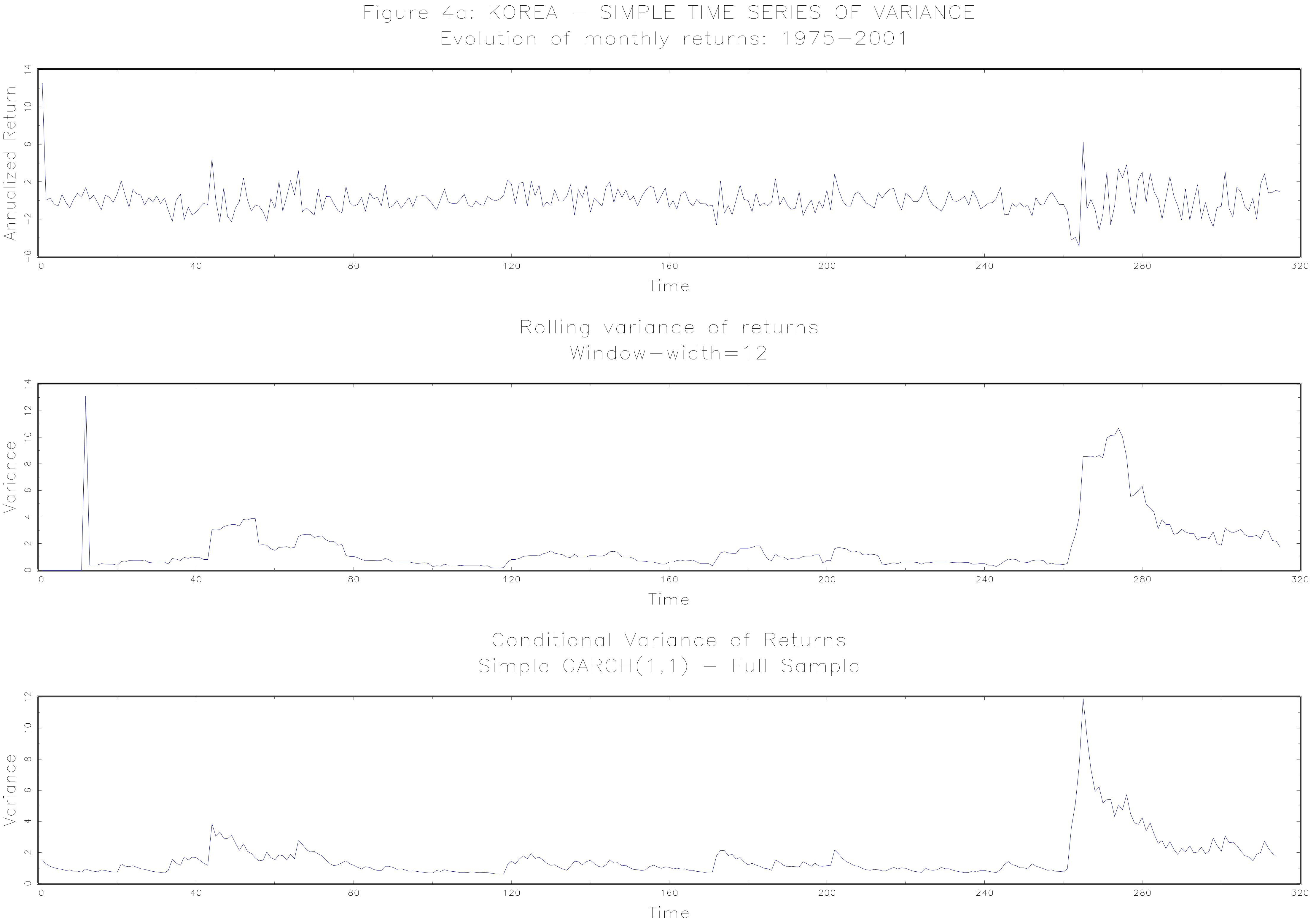


Figure 4a: KOREA – SIMPLE TIME SERIES OF VARIANCE
Evolution of monthly returns: 1975–2001
Annualized Return
Time
Rolling variance of returns
Window–width=12
Variance
Time
Conditional Variance of Returns
Simple GARCH(1,1) – Full Sample
Variance
Time

Figure 5a: MEXICO – SIMPLE TIME SERIES OF VARIANCE

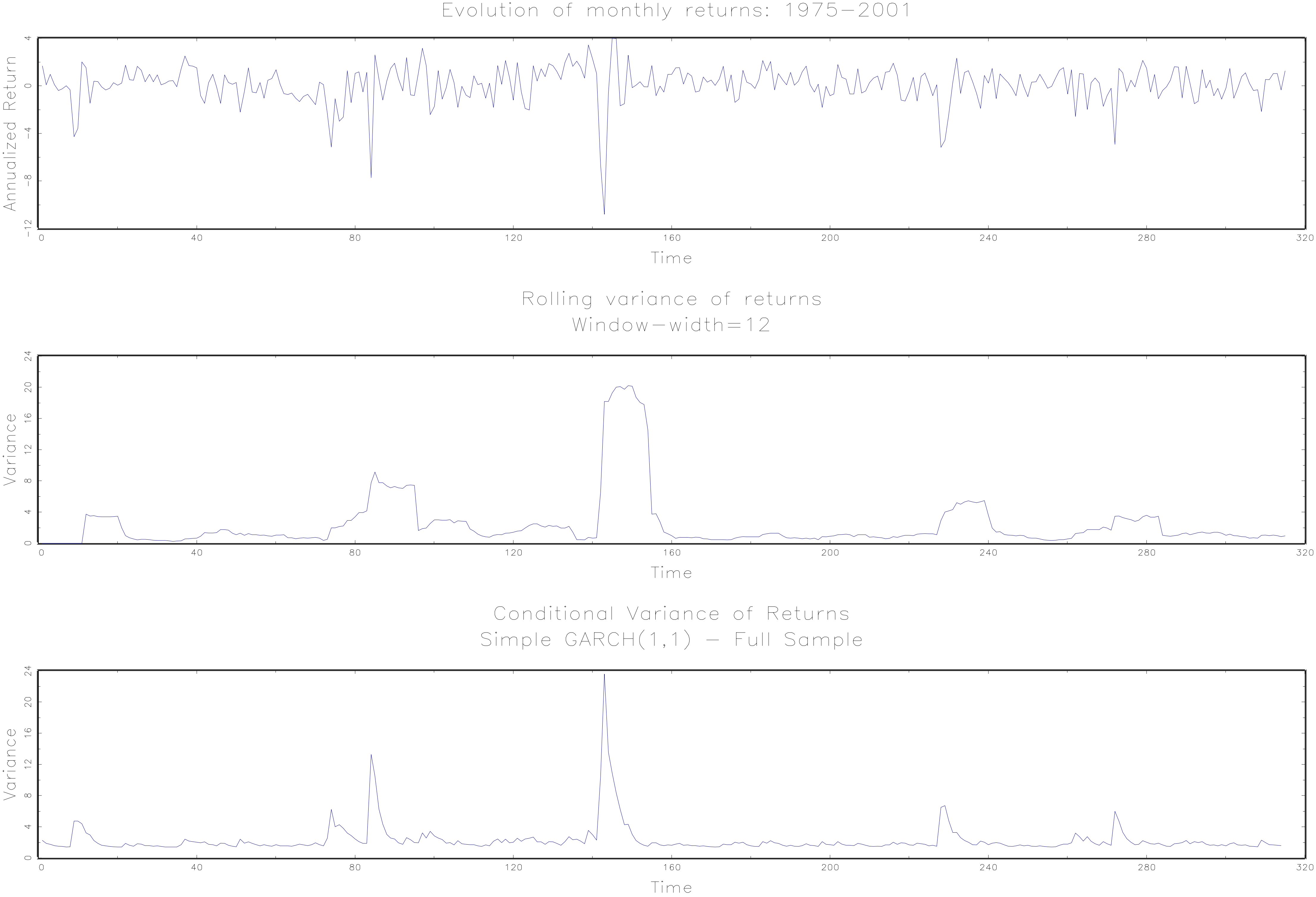


Figure 6a: THAILAND – SIMPLE TIME SERIES OF VARIANCE
Evolution of monthly returns: 1975–2001