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Changes in the Dynamic Behavior of Emerging Market Volatility: Revisiting the Effects of Financial Liberalization

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ABSTRACT

In this paper we test whether the dynamic behavior of stock market volatility in six emerging economies has changed over the period 1976:01-2004:12. This period corresponds to years of profound development of both the financial and the productive sides in these emerging countries, but also to the years of the major financial crises. Our analysis suggests that changes in volatility behavior, while indeed present, may have been overstated in the past: simple specifications account for most of the dynamics of stock market volatility and therefore become powerful tools for volatility analysis. Additionally, we show that financial liberalization of emerging markets has generally reduced the level of market volatility and its sensitivity to news.

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1 Introduction

The last decades have witnessed a substantial development of financial markets, in both developed and emerging economies. 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.

During the late 1980s and early 1990s several Latin America and Asian economies went through a number of economic reforms, financial liberalization and global integration processes. However, these processes of financial liberalization and economic reform have been tempered by recent financial crises. The crises and other instances of extreme financial instability illustrate possible risks of 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 markets have experienced significant increases in volatility -i.e. increased instability- in the post-financial liberalization era.

Given this interest in emerging market instability, many authors have tried to assess the effect of financial reforms on diverse features of emerging markets (e.g., Bekaert and Harvey, 2000; Henry, 2000; Bekaert et al., 2002a, 2002b; Edison and Warnock, 2003). For example, in a recent paper Bekaert et al. (2006) compellingly show how financial liberalization and capital account openness have significantly reduced the volatility of economic growth. Stock return volatility is another feature that has received wide attention, probably due to the above mentioned criticisms that have blamed increased instability on the financial reform processes. Examples of analyses of emerging market volatility are Bekaert and Harvey (1997), De Santis and Imrohorglu (1997), Huang and Yang (1999), Kim and Singal (2000), Aggarwal et al. (1999), Kaminsky and Schmuckler (2003) and Edwards et al. (2003). These recent papers have used increasingly sophisticated statistical techniques in order to dissect the behavior of volatility, although the improvement in explanatory power over that of simpler methodologies seems to be small.

In this paper we focus on analyzing whether the dynamic behavior of stock market volatility has changed significantly over the period 1976-2004 for six emerging countries. The choices of countries and period make the analysis especially relevant. Our sample period includes the financial liberalization 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 have led to these changes. Additionally, we show the power of simple statistical models to account for the evolution of volatility in emerging stock markets.

We are therefore particularly interested in addressing the following questions:

- How has the volatility of the stock market behaved in six emerging countries in the last two and a half decades?
- Has the dynamic behavior of stock market volatility changed through time?

Are simple statistical models enough to account for the evolution of volatility in emerging economies?

- Is it possible to find a relationship between changes in emerging stock market volatility and the financial liberalization processes? In what direction?

We begin with a descriptive look at the data: we estimate some statistics of stock market volatility and present a simple nonparametric measure which tracks the evolution of stock market volatility over time. This empirical analysis, along with the history of events, suggests the existence of structural changes in the statistical model driving the volatility of stock returns, and we proceed to identify these changes and explain what they imply for the evolution of stock market volatility. Since we do not want to impose the dates of the breaks, we use methodologies of detection of endogenous breakpoints.

The structure of the paper is as follows. Section 2 briefly reviews some of the previous contributions on the relationship between financial liberalization and stock market volatility. Section 3 uses data on six emerging stock markets to show the excellent performance of simple volatility models when tracking the evolution of volatility in these markets. In Section 4, we use methodologies that have been recently proposed in order to locate changes in the dynamic structure of stock market variance. We provide a brief discussion of the results in the context of our analysis. Finally, in Section 5 we offer some concluding remarks.

2 Financial Liberalization and Stock Market Volatility

Since the mid 1980s, many emerging countries have been involved in financial integration and liberalization processes. According to finance literature, stock market volatility could either 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 efficient, thus leading to higher - though less persistent- volatility as prices react fully and more quickly to relevant information; also, increased volumes of speculative capital may induce excess volatility. On the other hand, in the pre-liberalization period there may be larger swings from fundamental values that lead to higher volatility and to a more intense reaction to shocks. After liberalization, the gradual development and diversification of the markets could lead to lower volatility and to a lower sensitivity to new information.¹ Additionally, given the evidence that volatility of some market fundamentals such as economic growth seems to decrease after liberalization (Bekaert et al., 2006), the previous effect is likely to be reinforced.

Considerable research has focused on stock market liberalization and stock market volatility and the empirical evidence is mixed. Bekaert and Harvey (1997) generally find that volatility decreases after liberalization. De Santis

¹Note that the arguments refer not only to the level of volatility but also to its behavior over time: persistence and impact of new information.

and Imrohorglu (1997) also find evidence that volatility decreased after liberalization in a subset of countries, such as Argentina. However, Huang and Yang (1999), using the dates of financial liberalization from De Santis and Imrohorglu (1997), 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 decreased in another four countries (Argentina, Chile, Malaysia and the Philippines).

These three papers take the dates of the structural changes as given, and then proceed to analyze the behavior of volatility pre and post-change. A related stream of literature has opted for not specifying a priori the dates of the breaks, which are instead estimated endogenously, either in parametric settings (mostly Markov switching processes: Edwards and Susmel, 2003) or through some non-parametric methodology (turning point detection, as in Edwards et al., 2003 or Kaminsky and Schmuckler, 2003 or pure endogenous breakpoint detection, as in Aggarwal et al., 1999). The results of these papers are also mixed. Edwards et al. (2003) find that volatility after financial liberalization has increased in Asian countries but not in Latin American countries. Aggarwal et al. (1999) find that most events around the time period when shifts in volatility occur are local but that liberalization processes seem not to have induced the changes in variance. Also, they find both increases and decreases in volatility depending on the country and on the sequence of events.

Thus, there is still not a clear answer on whether financial liberalization leads to significant changes in the behavior of volatility and in what direction these changes occur. Furthermore, most of the literature so far has focused on detecting changes in the unconditional level of the variance. However, little attention has been paid to the fact that changes in unconditional volatility may come from changes in its dynamic behavior -persistence, effect of new information-. We attempt to give a further step in this direction by looking for possible changes in a richer structure of volatility behavior.

3 Volatility Behavior in Some Emerging Stock Markets

3.1 A First Look at the Data

In this section we use long series of 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.² The series run from

²These indexes, formerly calculated by the IFC, are dollar denominated price indexes of the stock markets in each country. We use the Global Index, 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.

1976:01 to 2004:12, thus yielding a total of 347 observations.³

We show some descriptive statistics of the emerging stock market returns and then move to a simple graphical analysis of volatility. Table 1 reports basic univariate statistics for the annualized regular returns of our six markets.⁴ Average returns during the sample period range between 1.4% in Brazil to 15.7% 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 had the most stable markets.

Insert Table 1

A simple look at the dynamic behavior of stock market volatility can be taken in Figure 1. The graphs show the evolution of stock returns during the sample period along with a nonparametric measure of return volatility, a 12-month rolling variance. This annualized rolling variance is calculated as follows:

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

where y_t is the return of the stock market index over period t and μ_{12} is the sample mean over the 12-month window.

Insert Figure 1 here

This rolling variance gives a first idea of the evolution of both the conditional and the unconditional variance of the different stock markets. We note that the graphs already suggest the existence of changes in the unconditional volatility –manifest in level shifts in the rolling variance: Argentina post-1990, Korea and Thailand post-1997, and maybe Chile post-1980. Other features that can be detected are the less frequent occurrence of high volatility periods in Latin American countries post-1990 and the apparent reduction in the duration of high volatility episodes across the board. The graphs identify episodes of extreme instability: in Argentina, stock market volatility presents a peak around 1989-1990, related to a period of hyperinflation and banking crises. In Brazil, after a continuous buildup, the peak in the stock market volatility happened between 1989 and 1991, coinciding with the Collor Plan –that introduced a new currency which was devalued shortly afterwards– and with several anti-inflation plans. For the Asian markets, the most volatile period was 1997, associated with their main financial crisis. Chile experienced the largest volatility during 1976, when a profound banking crisis and the breakdown of the entire mortgage system took place. Finally, the most volatile period in Mexico, 1987-1988, coincides

³Data availability and comparability also dictated the final 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 different methodologies used by the countries. Still, one would ideally use as long a series as possible.

⁴We calculate regular returns as $r_t = 12(\log P_t - \log P_{t-1})$.

with the Pacto de Solidaridad Social, another price stabilization plan aimed at controlling inflation rates. Thus, most of the episodes of instability seem to be inherently local in nature and short-lived, and have been associated with stabilization plans in Latin America. It is the case that after these plans, the markets seem to have become significantly less volatile.

3.2 GARCH models of Emerging Stock Market Volatility

We give now a more formal structure to the evolution of stock market volatility using simple GARCH models. These statistical specifications have been successfully applied to financial data and have become a popular tool to study financial market volatility. In a simple GARCH(1,1) process, the stock returns and the variance of innovations to stock returns are given by:

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

The three parameters in the variance equation have intuitive interpretations. ϖ_0 drives the level of the variance. The other two parameters determine the dynamic behavior of the series: α_1 can be interpreted as the persistence and α_2 as the impact in volatility of new information.⁵ In the next section we allow for changes in all three parameters, thus explicitly looking at a more complete dynamic behavior of volatility: a change in any of the three parameters would generate a change in the level of unconditional volatility, but the meaning of changes in the three parameters is obviously different.⁶

We have fitted GARCH(1,1) models to our series of returns, with μ_t assumed to be an AR(1) process (see Table 2). The parameters of the estimation appear in Table 2. The table also presents the unconditional variance implied by the estimates. The series of conditional variances –found using the recursion $\sigma_t^2 = \widehat{\varpi}_0 + \widehat{\alpha}_1 \sigma_{t-1}^2 + \widehat{\alpha}_2 u_{t-1}^2$ with the estimated parameters and some initial value for u_0 – are shown in Figure 2, along with the rolling variances from Subsection 3.1. The comparison is quite striking and it already gives the first important insight of our analysis: a simple GARCH model with three parameters captures the evolution of volatility surprisingly well, without resorting to complicated specifications with breakpoints or additional parameters. In fact, we will see that the inclusion of structural breaks –we noted that some level shifts are apparent in the series of returns, thus hinting at possible structural breaks– does not necessarily improve the fit of the evolution of volatility. In other words, the GARCH(1,1) model for volatility appears as a simple yet very powerful tool for volatility prediction, even in apparently complicated settings such as emerging financial markets undergoing development processes. This result is

⁵ $\alpha_1 + \alpha_2$ is usually interpreted as the persistence of the variance, although it is more exactly the persistence parameter of the process for squared returns implied by the GARCH structure. We believe that an interpretation of α_1 as persistence of the variance is slightly more intuitive.

⁶The unconditional variance of the series implied by the GARCH structure is $\varpi_0 / (1 - \alpha_1 - \alpha_2)$.

quite encouraging for practitioners and stock market analysts, who can profit from the well-accepted and intuitive GARCH specification without a significant loss of explanatory power.

Insert Table 2 here

Insert Figure 2 here

4 Structural Breaks in Emerging Stock Market Volatility

In order to take a deeper look at the possible existence of changes in the variance of emerging stock markets, we use now methodologies designed to locate changes in the level of unconditional variance and in its dynamic properties.

4.1 Locating Structural Breaks in a GARCH Setting

Building on the analysis in Section 3.2, we propose a testing methodology based on the location of endogenous structural breaks that focuses on changes in the parameters in the variance equation of the GARCH setting. 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 estimation of the number and location of multiple endogenous structural breaks is still 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). The techniques in the referenced papers have been developed for estimation and location of endogenous breaks in the mean parameters of trend models but, as Bai and Perron (1998) mention, they can accommodate changes in the variance.

We use the general framework in Bai and Perron (1998, 2003a, b) and their procedure of sequentially locating the breaks with the 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 this null is rejected, 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 $\mathbf{t} = \{t_1, t_2, \dots, t_l\}$ 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,

$$L(\mathbf{t}, \theta) = -\frac{1}{2} \left\{ \sum_{t=1}^{t_1} \left[\log \sigma_{1,t}^2 + \frac{\widehat{u}_{1,t}^2}{\sigma_{1,t}^2} \right] + \sum_{t=t_1+1}^{t_2} \left[\log \sigma_{2,t}^2 + \frac{\widehat{u}_{2,t}^2}{\sigma_{2,t}^2} \right] + \dots + \sum_{t=t_l}^T \left[\log \sigma_{l,t}^2 + \frac{\widehat{u}_{l,t}^2}{\sigma_{l,t}^2} \right] \right\} \quad (3)$$

where $u_{i,t}$ is the filtered return process and $\sigma_{i,t}^2 = \varpi_{0,i} + \alpha_{1,i} \sigma_{t-1}^2 + \alpha_{2,i} \widehat{u}_{t-1}^2$.

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:

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

where $\mathbf{t} = \{t_1, t_2, \dots, t_l\}$ is the first set of l breaks (under the null of no additional break) and $\mathbf{t}^* = \{t_1, t_2, \dots, t_{l+1}\}$ is the set of $l + 1$ breaks that includes τ as a new possible time for a break. $L(\mathbf{t}, \widehat{\theta}(\mathbf{t}))$ 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:

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

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

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

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 et al. 1998, Bai and Perron, 1998, 2003a,b) have a limiting distribution that depends on the number of parameters q 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 (Bai and Perron, 1998). These critical values are found by simulation.

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 $\mathbf{t} = \{t_1, t_2, \dots, t_l\}$ 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. 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.⁷

The critical values for 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 null hypotheses of no break) in Table 3 along with the estimated values of the sup $-LR$ tests for the six countries in our analysis.

Insert Table 3 here

4.2 Empirical Results of the Endogenous Break Analysis

We comment now on the results of the likelihood-based estimation. Parameter estimates are shown in Table 4, only in the cases where a significant break has been found. The table presents the parameters and standard errors of the two subsamples determined by the break, the date of the break and the unconditional variance implied for each subsample.

Insert Table 4 here

The main results can be summarized as follows. First, we detect that there has been one structural change in the stock market volatility of four of the six countries, whereas Brazil and Korea present no break. As we show in Figure 1, Brazil presents a triangular trending behavior of volatility which suggests that the dynamic behavior of volatility has been similar through time, and it is just the occurrence of more frequent large shocks around the liberalization date, located around the peak, that generates the smooth increase –and subsequent decrease– in volatility.⁸ Evidence for a second break was weak or nonexistent, so we do not comment on that analysis.

The break dates detected are 1991:05 for Argentina, 1983:03 for Chile, 1997:12 for Mexico and 1989:01 for Thailand. The break dates are close to those of financial liberalization –see Table 5 for the dates used by some authors– for Argentina and Thailand, whereas in the case of Chile the decrease in variance in the early 1980s associated with the stabilization plans is detected, instead.

⁷Notice that the procedure outlined above is *sequential* in nature. An alternative –and also consistent– 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.

⁸In the case of Brazil, the value of the test is close to significance, but the parameter estimates of the second subperiod –determined by the 1999 crisis– are quite unstable, due to the few observations available. Future availability of further data might qualify this result. The case of Korea is especially interesting. In a previous version of this paper that had data up to 2002:03, a break was detected at the time of the Asian flu. Inclusion of almost two years of additional data has deemed this break not significant: a single set of parameters seems to capture well the evolution of volatility both before and after the crisis. The old analysis where fewer observations after 1997:10 were available probably was too influenced by the turmoil around the crisis, which distorted the estimates of the post-crisis parameters. This gives still more strength to the conclusion that a simple GARCH model can capture the behavior of volatility better than more complicated specifications.

It is interesting to take a look at some of the economic and political events associated with those breaks, since the evidence suggests that both liberalization and stabilization policies tended to be adopted around those dates.

The break in Argentina in 1991 also coincides with the adoption of the Convertibility Plan, which established the currency board and the one-to-one fixed conversion rate with the dollar. Furthermore, a deregulation in the domestic industry and external trade –along with that of the capital markets– also took place in 1991. Thus, markets seem to have reacted –positively, as we will comment later– to stabilization and liberalization measures in Argentina. The break in Chile comes with the government decision to maintain a “competitive” real exchange rate by adopting a trending crawling band for the peso–dollar dollar rate. This exchange rate policy was complemented by an antiinflationary policy based on interest rate targeting. Again, financial markets rewarded these stabilization measures with lower levels of volatility. Mexico implemented a stabilization policy in 1988, pegging the peso to the dollar with a fluctuation band. This exchange rate peg was consciously adopted to provide the anchor that would prevent an inflation of the currency. As we note later, there is some mild evidence that this stabilization policy, that again coincided with financial liberalization, brought about a reduction in volatility, but the turmoil generated by the Asian crisis seems to be clouding this result (more on Mexico later). Finally, the case of Thailand is again one in which the liberalization date is associated with a significant change in volatility behavior. In the mid-1980s, the Thai economy began to grow rapidly and shortly afterwards it began the process of liberalization of its financial system. As part of this process, Thailand began to lift capital controls in 1990 so funds could flow freely in and out of the country. The results for Thailand would indeed signal another reduction in volatility coming after liberalization if one could discard the effects of the Asian crisis.

A closer look at the parameter values and implied dynamic behavior suggests, most importantly, that for Argentina and Chile the unconditional variance has decreased significantly after financial liberalization. The result for Mexico and Thailand suggests an increase in volatility, mostly due to the high persistence implied by the estimated parameter (1.03 for Mexico and 0.82 for Thailand) and to the fact that the Asian flu is contained in the second subperiod. The case of Mexico is slightly puzzling. In previous versions of the paper –with a slightly shorter data series– the break was detected around the date of financial liberalization plus stabilization and the results were parallel to those of Argentina. However, the behavior of returns in the last few periods –of extreme persistence– seems to have influenced the parameter estimates, which are actually quite non-standard and suggest an aberrant period more than a permanent change in behavior. We believe these results for Mexico have to be taken with care, and we remind the reader about the earlier results, where the break for Mexico and the behavior implied by the parameters suggested that liberalization reduced the volatility and the sensitivity to news of the Mexican stock market.⁹

⁹This hints at the importance of developing estimation methods that account for outly-

The implications regarding the dynamic behavior of volatility are quite interesting. Argentina, Mexico and Thailand present an increase in the persistence of volatility (α_1), whereas Chile, on the other hand, presents a higher persistence in the first period. Thus, there does not seem to be a clear direction for the effect, although a higher persistence of volatility seems to come after liberalization. The results are consistent across countries, however, with respect to the parameter of sensitivity to new information (α_2). In all cases, the absolute value of this parameter has fallen after liberalization –or after the break in the case of Mexico. In other words, emerging markets react less intensely to shocks or new information as they develop or liberalize. Although the shocks these markets receive may be larger –there are instances of very large returns in the post-liberalization period– more open and liberalized emerging markets react less dramatically to these shocks.

Thus, liberalization seems to have had positive effects on the volatility of emerging markets, and these effects come mainly from the reduced sensitivity to new information: volatility may be more persistent, and larger shocks may hit the market, but the market reacts less intensely, thus leading in some cases to a reduced unconditional level of volatility –as it happens with Argentina and Chile– and, in any case, to smaller peaks of high volatility. This result is consistent with the second argument outlined in Section 2: before liberalization, poorly developed and shallow markets may suffer large swings from fundamental values that lead to higher volatility and to overreaction to shocks. After liberalization, more developed and diversified markets should then experience lower volatility and a lower sensitivity to new information. If, additionally, fundamentals are less volatile after liberalization (Bekaert et al., 2006), then the reduction in stock market volatility should be even more noticeable.

Insert Table 5 here

Figure 3 shows, in the four cases where the break is significant, the comparison between the GARCH-fitted conditional variance that includes the break and the rolling variance from Section 3. It can be seen that the GARCH-with-break variances do not add much to the fit already provided by the simple GARCH(1,1). This again gives support to the use of simple GARCH models –maybe coupled with some detection of outliers– for the analysis of volatility.

Insert Figure 3 here

4.3 Cumulative Sums (CUSUM) - Based Tests for Structural Breaks in Variance

We present now the results of three alternative tests for endogenous breaks based on cumulative sums (see the Appendix for a brief description of the tests). The three tests are similar in spirit and rely on the fact that if there is a level shift

ing observations or periods (see Johansen and Sornette, 2001, Charles and Darne, 2005, or Rodrigues and Rubia, 2005, for recent work along this line).

in the variance of the series, cumulative sums of returns should depart at some point from what would be implied by uniform behavior over the full sample. These tests have been used before for the detection of breaks in emerging market variance (Aggarwal et al., 1999).

The first two tests were developed by Kokoszka and Leipus (KL, 2000) and Inclan and Tiao (IT, 1994). 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 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 Both tests are directly applied on the return process using the squared or the absolute returns and assume that the returns have no structure in the mean. The third test (Chen et al., CCZ, 2005) seeks to be more robust to the mean structure of the series, since it is based on the residuals from a first-stage estimation of the mean μ_t . The test is done on $\widehat{W}_t = r_t - \widehat{\mu}_t$, where $\widehat{\mu}_t$ could be a nonparametric estimator of μ_t (e.g. a kernel smoother or a local linear regression estimator).

We carry out the three tests on both the regular r_t and AR(1) demeaned returns ($\widehat{u}_t = r_t - \widehat{\phi}_0^{ols} - \widehat{\phi}_1^{ols} r_{t-1}$). Tables 6-8 report the results. We have carried out the KL and IT tests for both the squared and the absolute regular and demeaned returns. As we can see in Table 6, the IT tests tend to find many breaks: for example, it locates seven breaks in Mexico and six in Argentina.¹¹ In most of the cases, the tests detect similar breaks in regular returns and demeaned returns. Finally, and most importantly, the breaks, when identified are associated with financial liberalization events in the case of Argentina, Chile and Mexico. In the case of Chile, it seems that the variance also changed (decreased) earlier in the sample, around the stabilization plans of the early 1980s and for Argentina and Thailand there is also evidence of changes in the years following the Asian crisis. For Korea and Thailand the tests agree on the Asian flu as the main moment of a change (increase) in variance. This suggests that the CUSUM-based tests may be highly sensitive to large realizations – outliers – of the stock returns, and therefore should be used with care when analyzing emerging stock markets, where large observations are frequent. For Brazil the tests do not agree. The trending behavior of the data for Brazil (see Figure 1) may be behind this apparent conflict among the tests.

¹⁰The IT test tends to give evidence of too many breaks (Aggarwal et al., 1999), especially in time series with GARCH effects.

¹¹Aggarwal et al. (1999) found evidence of structural breaks in the variance of all the series they analyzed, and sometimes the breaks were very frequent: in the case of Argentina, they find evidence of ten breaks in a total of ten years of data (p. 45). This finding is easy to interpret in the light of our discussion, and when one looks at graphs in the original paper that represent the returns along with the estimated variances. The breaks are detected by using cumulative sums of squares of returns, so large outlying returns cause the appearance of the break. The authors find that when a dummy variable is included for the whole period until the next break (i.e. until the next big return signals a break) GARCH-type effects disappear. This should be expected given that the effect of the outlying return would be accounted for in the variance equation by the period-by-period dummies.

As a robustness check, these tests generally agree with the results of the likelihood analysis. However, given that they impose less structure on the behavior of volatility, they are also less powerful when analyzing changes in variance of financial time series, where we have already seen that the GARCH specification can account for the evolution of volatility without resorting to breaks. Further development of these intuitive CUSUM tests that makes them more robust –e.g. along the lines of Rodrigues and Rubia, 2005– seems to be necessary before they can be confidently used with emerging stock market data.

Insert Tables 6 - 8 here

5 Conclusions

In this paper we have looked at the evolution of volatility in six representative emerging stock markets, placing the results in the context of the financial liberalization processes these countries went through during the 1980s and 1990s. In particular, we looked at whether structural breaks are necessary to account for the evolution of stock market volatility and whether these breaks were associated with liberalization processes.

Our analysis suggests, first, that the extent of changes in volatility behavior may have been overstated in previous research. We show how simple GARCH models can give as good a fit to the evolution of volatility as complicated specifications with breaks. This makes GARCH models a powerful yet simple tool for volatility analysis that can be used by practitioners and stock market analysts.

We find that changes in volatility, when present, have indeed been associated with financial liberalization in the cases of Argentina, Chile and maybe Mexico –with a decrease in the volatility– and with Thailand –in this case, it seems that liberalization also reduced volatility, although the evidence is not as clear given that the Asian crisis contaminates the second subperiod. In other words, financial liberalization seems to have had some structural effects generally associated with reductions in market volatility. Of course, liberalization means that the markets may be more open to large shocks. This has led some to suggest increased volatility after liberalization, but we believe the correct interpretation would be one of lower average volatility although subject to the possibility of occasional large shocks.

Changes in the dynamic behavior of volatility are behind the latter result. In all cases we find a reduction in the impact of new information –that is, markets react less intensely to news– associated with the development or liberalization of the stock market. Persistence of volatility shows less uniform results across countries. This result suggests that a swings-from-fundamentals explanation of volatility may have merit: after liberalization, the enhanced depth of the financial market allows for less volatile movements in stock prices, and better interpretation of new information.

Global events impact all countries, but this impact is generally short lived and does not cause structural changes in the economies. Only Korea and maybe

Thailand seem to have suffered a permanent change around the time of the Asian flu, which can indeed be considered a global event. The case of Thailand, however, is less clear, since the change in volatility is located as early as in 1988, closer to the liberalization date. Therefore, it seems that changes in the structure and level of volatility/instability come mainly from local events, which in most cases are indeed associated with financial liberalization processes.

Our results open up interesting lines of research, both theoretical and empirical. Of special interest are the reasons behind the changes in volatility persistence and the reduction of the effect of news, or why Asian markets seem to be different from those in Latin America. One related question is the relative importance of liberalization and stabilization: most Latin American markets implemented strong stabilization policies at the time of liberalization, and this strategy seems to have paid off. Finally, our set of countries was determined by the availability of long time series. The analysis of a slightly shorter time span would allow for the observation of a larger set of countries and complement or qualify our results.

6 Appendix: The Three CUSUM-Type Tests for Structural Breaks in Variance

These three tests are all based on a similar principle: if there are breaks in the variance, properly standardized cumulative sums should at some point diverge. The tests we use were developed by Inclan and Tiao (IT, 1996), Kokoszka and Leipus (KL, 2000) and Chen et al. (CCZ, 2005).

The KL test of a break in the variance of a return series r_t assumes that r_t is a zero-mean process (possibly) conditionally heteroscedastic. The test is constructed by first calculating the series of cumulative sums

$$U_T(k) = \left(1/\sqrt{T}S_k - k/(T\sqrt{T})S_T\right) \quad (7)$$

where $S_k = \sum_{t=1}^k X_t$ and X_t 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 taken to be the index of the maximum of the values of the test. The asymptotic distribution of the normalized test

$$KL = \sup \{|U_T(k)|\} / \hat{\sigma} \quad (8)$$

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.¹²

The IT test assumes that the return series has a constant conditional variance (i.e. $r_t \rightarrow N(0, \sigma^2)$) and thus appears to be less appropriate in financial time series contexts. The test is constructed with a different transformation of

¹²We use a Newey-West heteroskedasticity and autocorrelation-consistent estimator of the long run variance, with truncation lag determined by the rule $4(T/100)^{2/9}$.

cumulative sums:

$$D_k = \left(\frac{S_k}{S_T} - k/T \right) \quad (9)$$

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:

$$IT = \sqrt{T/2} \max_k D_k \quad (10)$$

The distribution of this rescaled IT test is the same as that of the normalized KL test.

The CCZ test seeks to be more robust to the mean structure of the series, since it is based on the residuals from a first-stage estimation of the mean μ_t . The test is done on $\widehat{W}_t = r_t - \widehat{\mu}_t$, where $\widehat{\mu}_t$ could be a nonparametric estimator of μ_t (e.g. a kernel smoother or a local linear regression estimator). We take both $\widehat{W}_t = r_t$ and $\widehat{W}_t = \widehat{u}_t$. The cumulative sums $S_k = \sum_{t=1}^k \widehat{W}_t^2$ and $S_{T-k} = \sum_{t=k+1}^T \widehat{W}_t^2$ are then used to construct the following series of estimators

$$V_T^v(k) = \left(\frac{k(T-k)}{T^2} \right)^{1-v} \left(\frac{1}{T-k} S_{T-k} - \frac{1}{k} S_k \right) \quad (11)$$

for $[\delta_T \cdot T] \leq k \leq [(1 - \delta_T) \cdot T]$, where $[x]$ is the truncated integer of x and $\delta_T = \frac{(\log T)^{3/2}}{T}$. Then the test statistic is the supremum of the series of rescaled tests

$$CCZ = \sup_k \frac{\sqrt{T} \widehat{\sigma}^2}{\widehat{\sigma}_{w^2}^2} V_T^v(k) \quad (12)$$

where $\widehat{\sigma}^2 = \sum_{t=1}^T \widehat{W}_t^2 / T$ and $\widehat{\sigma}_{w^2}^2$ is an estimator of the long-run variance of \widehat{W}_t^2 .¹³ The distribution of this test depends on the value assumed for v . We use $v = 0$, for which the critical values are the same as those of the *KL* and the *IT* tests.

All three 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 $\sup U_T$, $\sup D_k$ or $\sup V_T^v$ of both subperiods is taken as the estimate of the second break, which in turn determines three subperiods and so on (see IT, 1994, for a description of the complete procedure).

References

- Aggarwal, R., Inclan, C., Leal, R., 1999. Volatility in emerging stock markets. *Journal of Financial and Quantitative Analysis* 34, 33-55.
- Andrews, D.W., Lee, I., Ploberger, W., 1996. Optimal changepoint tests for normal linear regression. *Journal of Econometrics* 70, 9-38.
- Bai, J., 1997. Estimating multiple breaks one at a time. *Econometric Theory* 13, 315-332.

¹³As before, we use a Newey-West estimator with truncation lag determined by the rule $4(T/100)^{2/9}$.

- Bai, J., 1999. Likelihood ratio tests for multiple structural changes. *Journal of Econometrics* 91, 299-323.
- Bai, J., Lumsdaine, R.L., Stock, J.H., 1998. Testing for and dating breaks in stationary and nonstationary multivariate time series. *Review of Economic Studies* 65, 395-432.
- Bai, J., Perron, P., 1998. Estimating and testing linear models with multiple structural changes. *Econometrica* 66, 47-78.
- Bai, J., Perron, P., 2003a. "Multiple structural change models: A simulation analysis" in Corbea, Durlauf and Hansen (eds.) *Econometric Essays in Honors of Peter Phillips*. Cambridge University Press: Cambridge.
- Bai, J., Perron, P., 2003b. Computation and analysis of multiple structural change models. *Journal of Applied Econometrics* 18, 1-22.
- Banerjee, A., Lumsdaine, R.L., Stock, J.S., 1992. Recursive and sequential tests of the unit root and trend-break hypotheses: Theory and international evidence. *Journal of Business and Economic Statistics* 10, 271-287.
- Bekaert, G., Harvey, C.R., 1997. Emerging equity market volatility. *Journal of Financial Economics* 43, 29-78.
- Bekaert, G., Harvey, C.R., 2000. Foreign speculators and emerging equity markets. *Journal of Finance* 55, 565-613.
- Bekaert, G., Harvey, C.R., 2002. Research in emerging market finance: Looking to the future. *Emerging Markets Review* 3, 429-448.
- Bekaert, G., Harvey, C.R., 2003. Emerging market finance. *Journal of Empirical Finance* 10, 3-55.
- Bekaert, G., Harvey, C.R., Lumsdaine, R.L., 2002a. Dating the integration of world equity markets. *Journal of Financial Economics* 65, 203-249.
- Bekaert, G., Harvey, C.R., Lumsdaine, R.L., 2002b. The dynamics of emerging market equity flows. *Journal of International Money and Finance* 21, 295-350.
- Bekaert, G., Harvey, C.R., Lundblad, C., 2006. Growth volatility and financial market liberalization. Forthcoming, *Journal of International Money and Finance*.
- Buckberg, E., 1995. Emerging stock markets and international asset pricing. *World Bank Economic Review* 9, 51-74.
- Charles, A., Darne, O., 2005. Outliers and GARCH models in financial data. *Economics Letters* 86, 347-352.
- Chen, G., Choi, Y.K., Zhou, Y., 2005. Nonparametric estimation of structural change points in volatility models for time series. *Journal of Econometrics* 126, 79-114.
- De Santis, G., Imrohorglu, S., 1997. Stock returns and volatility in emerging financial markets. *Journal of International Money and Finance* 16, 561-579.
- Edison, H., Warnock, F., 2003. A simple measure of the intensity of capital controls. *Journal of Empirical Finance* 10, 83-105.
- Edwards, S., Gómez Biscarri, J., Pérez de Gracia, F., 2003. Stock market cycles, financial liberalization and volatility. *Journal of International Money and Finance* 22, 925-955.

- Edwards, S., Susmel, R., 2003. Volatility dependence and contagion in emerging equity markets. *Journal of Development Economics* 66, 505-532.
- García, R., Perron, P., 1996. An analysis of the real interest rate under regime shifts. *Review of Economics and Statistics* 78, 111-125.
- Ghysels, E., Guay, A., Hall, A., 1997. Predictive tests for structural change with unknown breakpoint. *Journal of Econometrics* 82, 209-233.
- Henry, P.B., 2000. Stock market liberalization, economic reform and emerging market equity prices. *Journal of Finance* 55, 529-564.
- Huang, B.N., Yang, C.Y., 1999. The impact of financial liberalization on stock price volatility in emerging markets. *Journal of Comparative Economics* 28, 321-339.
- Inclan, C., Tiao, G., 1994. Use of cumulative sums of squares for retrospective detection of change of variance. *Journal of the American Statistical Association* 89, 913-923.
- Johansen, A., Sornette, D., 2001. Large stock market price drawdowns are outliers. *Journal of Risk* 4, 69-110.
- Kaminsky, G., Schmukler, S. 2003. Short-run pain, long-run gain: The effects of financial liberalization. *NBER Working Paper* 9787.
- Kim, E.K., Singal, V., 2000. Opening up of stock markets: Lessons from emerging economies. *Journal of Business* 73, 25-66.
- Kokoszka, P., Leipus, R., 2000. Change-point estimation in ARCH models. *Bernoulli* 6, 1-28.
- Lumsdaine, R.L., Papell, D.H., 1997. Multiple trend breaks and the unit root hypothesis. *Review of Economics and Statistics* 79, 212-218.
- Rodrigues, P.M.M., Rubia, A., 2005. On the effects of outliers in the asymptotic distribution of CUSUM tests for structural breaks in variance. Mimeo.

Table 1

Some basic statistics of the returns, 1976:01-2004:12

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	0.14	0.031	0.157	0.0757	0.099	0.049
SD	2.56	1.85	1.133	1.43	1.52	1.27
SK	0.073	-0.474	0.32	2.1	-2.07	-0.09
κ	8.74	5.97	5.08	20.1	13.48	6.51
ρ_1	0.031	0.009	0.154**	0.052	0.24**	0.083
Q(4)	1.36	2.461	19.34**	1.55	19.59**	13.9**
ARCH(4)	27.41**	8.94*	12.25**	54.6**	43.3**	49.3**
JB	478.25**	141.2**	68.92**	4494**	1839**	179.2**

Table 2

GARCH(1,1) model for the stock return volatility, 1976:01-2004:12

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon_t \quad \varepsilon_t \longrightarrow \text{nid}(0, \sigma_t^2) \text{ [Mean equation]}$$

$$\sigma_t^2 = \omega_0 + \alpha_1 \sigma_{t-1}^2 + \alpha_2 \varepsilon_{t-1}^2 \text{ [Variance equation]}$$

y_t is the regular (r_t) or the filtered (\hat{u}_t) 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 assuming Gaussian distributions for ε_t . The sample size is 347 months.

	β_0	β_1	ω_0	α_1	α_2	U.V.
Argentina						
r_t	0.098 (1.01)	0.092 (1.18)	0.175 (0.4)	0.797 (5.03)	0.199 (0.65)	38.34
Brazil						
r_t	0.001 (0.01)	0.079 (1.26)	0.082 (0.47)	0.855 (15.4)	0.119 (1.08)	3.19
Chile						
r_t	0.119 (2.44)	0.187 (3.92)	0.015 (0.17)	0.895 (4.72)	0.101 (0.19)	4.08
Korea						
r_t	0.11 (1.77)	0.061 (1.03)	0.122 (0.52)	0.764 (6.99)	0.147 (1.00)	1.37
Mexico						
r_t	0.096 (1.28)	0.197 (2.67)	0.185 (0.38)	0.76 (2.21)	0.166 (0.48)	2.49
Thailand						
r_t	0.03 (0.56)	0.077 (1.29)	0.072 (0.43)	0.769 (7.44)	0.179 (1.13)	1.39

Table 3
Likelihood-based tests ($supLR(l + 1|l)$).

	Test and Critical Values	
	α	$l = 0$
Critical Values for change in 3 params.	90%	13.43
	95%	15.37
	Argentina	34.81
	Brazil	15.03
	Chile	15.27
	Korea	8.91
	Mexico	25.58
	Thailand	21.97

The critical values come from Table II, Bai and Perron (1998). Only results on tests for $l=0$ (i.e. one structural break) are shown. Evidence for a second break is weak in cases where it can be estimated. Those results are available from the authors.

Table 4

GARCH(1,1) model with one break in GARCH parameters for the stock return volatility, 1976:01-2004:12

$$y_t = \beta_0 + \beta_1 y_{t-1} + \varepsilon_t \quad \varepsilon_t \longrightarrow \text{nid}(0, \sigma_t^2) \text{ [Mean equation]}$$

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

y_t is the regular (r_t) or the filtered (\hat{u}_t) 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 assuming Gaussian distributions for ε_t . The sample size is 347 months. UV denotes the unconditional variance. Coefficients of the mean equation are not shown, but are available upon request. Parameters have been found by estimating separately the two subsamples.

	ω_{01}	α_{11}	α_{21}	ω_{02}	α_{12}	α_{22}	UV ₁	UV ₂	Break	Test
Argentina										
r_t	1.85 (1.73)	0.61 (2.4)	0.205 (1.54)	0.203 (0.74)	0.833 (4.21)	0.045 (0.64)	10.0	1.66	1991:05	34.8
Chile										
r_t	0.063 (1.19)	1.08 (6.89)	-0.1 (-0.8)	0.136 (1.15)	0.769 (4.58)	0.058 (1.38)	3.28	0.78	1983:03	15.27
Mexico										
r_t	0.458 (1.68)	0.62 (3.17)	0.203 (1.64)	-0.03 (-0.6)	1.03 (6.8)	-0.02 (-0.3)	2.59	2.95	1997:12	25.58
Thailand										
r_t	0.143 (2.31)	0.406 (2.71)	0.445 (2.15)	0.115 (1.22)	0.821 (8.98)	0.123 (1.73)	0.96	2.05	1989:01	21.97

Table 5
 Different Liberalization dates across authors

Country	Bekaert and Harvey (2000)	Kim and Singal(2000)	Buckberg (1995)	Earliest
Argentina	1989:11	1989:11	1991:10	1989:11
Brazil	1991:05	1991:05	1991:05	1988:03
Chile	1992:01	1987:09	1989:10	1987:05
Korea	1992:01	1992:01	NA	1987:06
Mexico	1989:05	1989:11	1989:05	1989:05
Thailand	1987:09	1988:08	NA	1987:09

Table 6
CUSUM-based Tests: Inclan and Tiao (1994)

	Regular returns r_t		Demeaned returns \hat{u}_t	
	$(r_t)^2$	$ r_t $	$(\hat{u}_t)^2$	$ \hat{u}_t $
	Break	Break	Break	Break
Argentina	1976:12		1976:12	
	1989:05		1989:05	
	1990:02	1990:03	1990:02	1990:03
	1992:09		1992:09	
			2001:01	
		2002:06		
Brazil	1982:11		1982:11	
	1989:01		1989:01	
	1992:07		1992:07	
Chile	1978:03		1978:04	
				1983:07
	1988:07	1988:06	1988:07	
Korea	1997:10	1997:08	1997:10	1997:08
	1999:01		1999:01	
	2001:12		2001:12	
Mexico	1977:02		1977:02	
	1982:01	1982:01	1982:01	
	1983:02		1983:02	
	1987:07		1987:10	
	1988:06	1988:06	1988:06	
	1994:12		1994:12	
	1999:05		1998:10	
Thailand	1979:05		1979:05	
	1987:08	1990:04	1987:08	
	1997:08		1997:08	1996:06
	2000:08		2001:02	

Only the dates of the identified breaks are provided: values of the test are available upon request.

Table 7
 CUSUM-based Tests: Kokoszka and Leipus (2000)

	r_t		\hat{u}_t	
	$(r_t)^2$	$ r_t $	$(\hat{u}_t)^2$	$ \hat{u}_t $
	Break	Break	Break	Break
Argentina	1990:01		1990:01	
Brazil				
Chile	1983:03		1983:07	
Korea				
Mexico				
Thailand	1996:09		1996:09	

Only the dates of the identified breaks are provided: values of the test are available upon request.

Table 8
 CUSUM-based Tests: Chen et al. (2005), $v = 0$.

	r_t	\hat{u}_t
	Break	Break
Argentina	1977:11	1977:11
	1992:09	1992:09
Brazil	1987:02	1987:02
	1993:06	1993:06
Chile	1978:11	1978:12
	1984:04	1984:08
Korea	1998:10	1998:10
	2002:07	2002:07
Mexico	1982:11	1982:11
	1989:06	1989:06
Thailand	1997:10	1997:07
		1999:06
	2001:10	2002:05

Only the dates of the identified breaks are provided: values of the test are available upon request.

Figure 1: Returns and Rolling Measure of Volatility

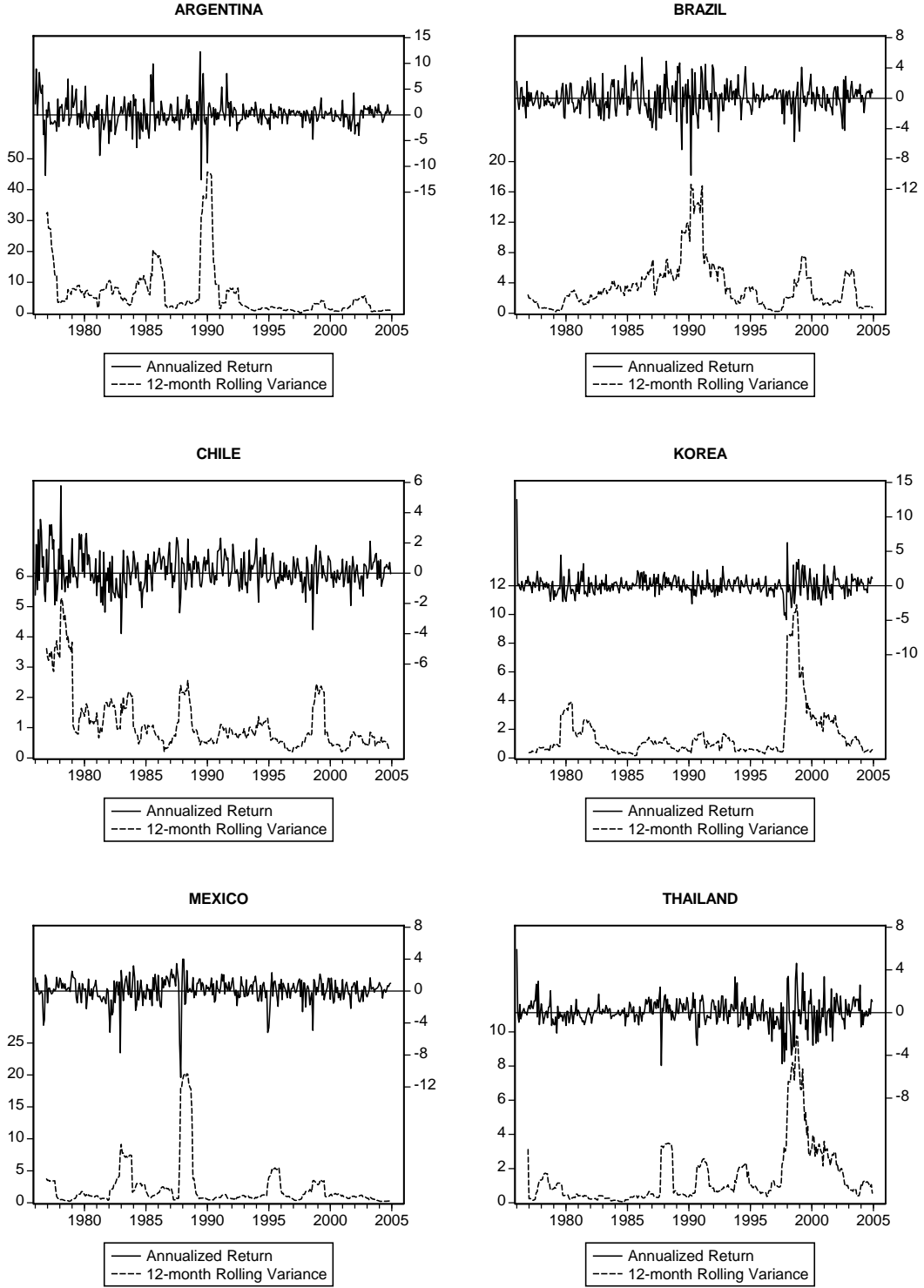
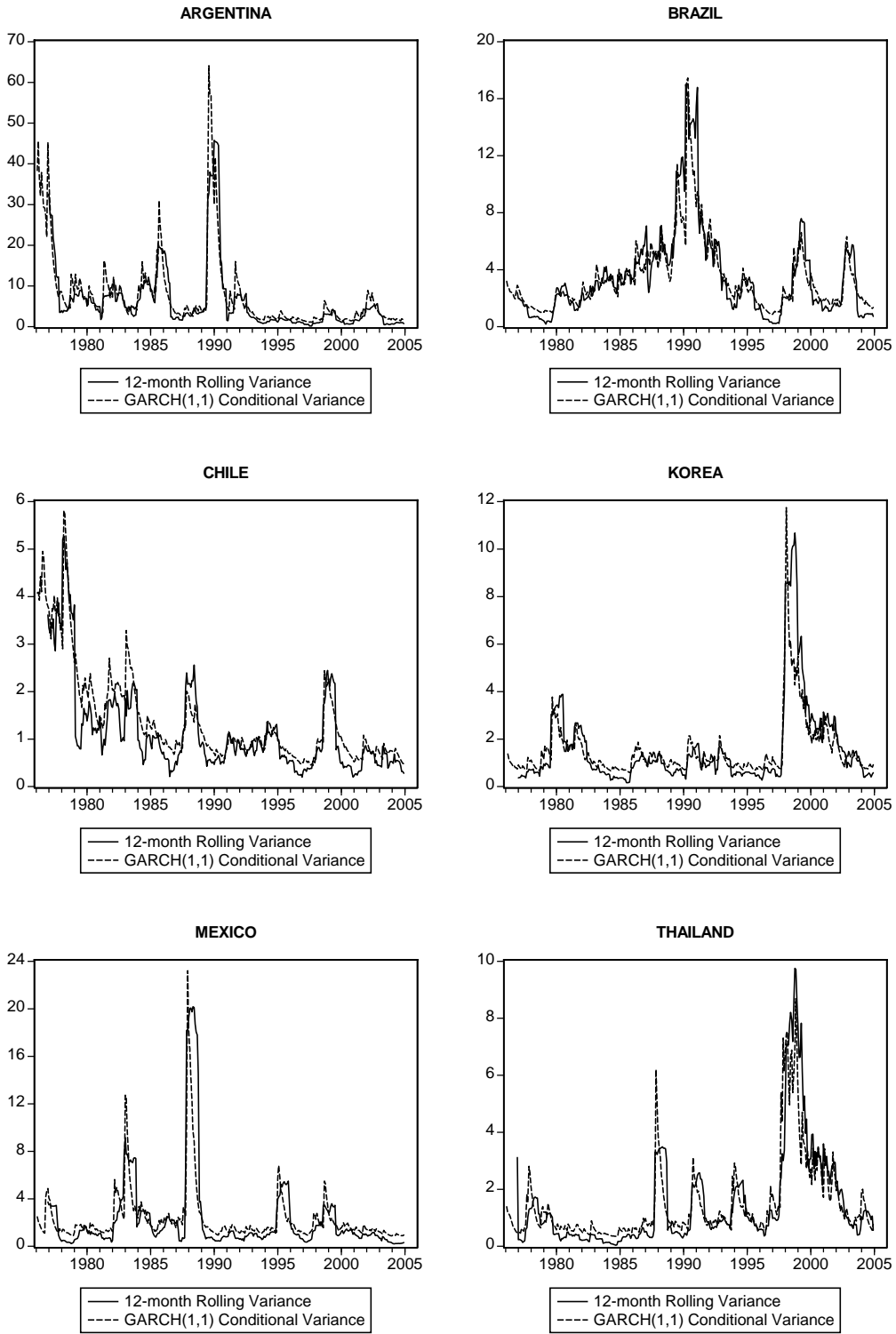


Figure 2: Rolling Variances and GARCH-fitted Conditional Variances



**Figure 3: Rolling Variances
and GARCH-with break Conditional Variances**

