VOLATILITY IN EMERGING STOCK MARKETS

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Abstract

This study examines what kinds of events cause large shifts in the volatility of emerging stock markets. We first determine when large changes in the volatility of emerging stock market returns occur and then examine global and local events (social, political, and economic) during the periods of increased volatility. An iterated cumulative sums of squares (ICSS) algorithm is used to identify the points of shocks/sudden changes in the variance of returns in each market and how long the shift lasts. Both increases and decreases in the variance are identified. We then identify events around the time period when shifts in volatility occur. Most events tend to be local and include the Mexican Peso crisis, periods of hyperinflation in Latin America, the Marcos-Aquino conflict in the Philippines, and the stock market scandal in India. The October 1987 crash is the only "global event" during the period 1985-1995 that caused a significant jump in the volatility of several emerging stock markets.

I. INTRODUCTION

It is well known that emerging stock markets are characterized by high volatility. This paper examines whether global or local events are more important in causing major shifts in emerging markets' volatility. We also examine whether these events tend to be social, political, or economic. Our goal is to give economic significance to changes in the level of volatility. The empirical approach taken in this paper is different from most of the previous literature.[1] We first detect shifts

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in volatility from the data, and then examine what events took place around that time period.

A procedure based on an iterated cumulative sums of squares (ICSS) is used to detect the number of (significant) sudden changes in variance in the time series, as well as to estimate the time point and magnitude of each detected sudden change in the variance. The procedure detects both increases and decreases in the variance. We examine ten of the largest emerging markets in Asia and Latin America, in addition to Hong Kong, Singapore, Germany, Japan, U.K. and U.S.; also included in the analysis are the Morgan Stanley World Index, the Far East Index, the Latin American Index and the Emerging Markets Index.

The high volatility of emerging markets is marked by frequent sudden changes in variance. The periods with high volatility are found to be associated with important events in each country rather than global events. The October 1987 crash is the only global event in the last decade that significantly increased volatility in several markets. Other events, such as the Gulf War, had little impact. The results are also consistent with Bekaert and Harvey (1997a) and Susmel (1997) who find that on average the proportion of variance attributable to world factors is quite small for emerging markets. Our results strongly support the findings of Bailey and Chung (1995) as we also find that important political events tend to be associated with sudden changes in volatility. The periods of increased volatility tend to be common to returns measured in local currency and dollar-adjusted returns. During the period of increased volatility, dollar-adjusted returns have higher standard deviations than local returns do, possibly reflecting additional volatility in exchange rates.

The rest of the paper is organized as follows. Section II describes how the ICSS algorithm is used to detect sudden changes in variance and describes the data set used for this study. Section III reports the results for sudden changes in variance that correspond to notable social, political and economic events. Section IV presents a summary and conclusions.

II. METHODOLOGY AND DATA

A. Detecting Points of Sudden Changes in Variance

As discussed earlier, our goal is to identify shifts in volatility first and then examine what local and global events occur around that time period. The methodology used in this study to detect discrete changes in the variance of an observed time series is based on the ICSS algorithm presented by Inclan and Tiao (1994). The analysis assumes that the time series of interest displays a stationary variance over an initial period, and then there is a sudden change in variance, perhaps driven by news impacting the financial markets. The variance is then stationary again for a time, until the next sudden change. This process is repeated through time, yielding a time series of observations with an unknown number of changes in the variance. Accordingly, let $\{\varepsilon_t\}$ denote a series of independent observations from a normal distribution with zero mean and with unconditional variance σ_t^2. The variance within each interval is denoted by τ^2_j, j = 0, 1, . . . , N_T, where N_T is the total number of variance changes in T observations, and $1 < \kappa_1 < \kappa_2 < ... < \kappa_{NT} < T$ are the set of change points.

(1)

$$
\begin{aligned}
\sigma_t^2 &= \tau_0^2 & 1 < t < \kappa_1 \\
&= \tau_1^2 & \kappa_1 < t < \kappa_2 \\
& & \cdots \\
&= \tau_{N_T}^2 & \kappa_{N_T} < t < T
\end{aligned}
$$

To estimate the number of changes in variance and the point in time of each variance shift, a cumulative sum of squares is used. Let $C_k = \sum_{t=1}^{k} \varepsilon_t^2$, k=1, . . . ,T, be the cumulative sum of the squared (mean centered) observations from the start of the series to the kth point in time. Then define the statistic D_k as follows:

$$D_k = (C_k/C_T) - k/T \qquad k = 1, \ldots, T \quad \text{with } D_0 = D_T = 0.$$

If there are no changes in variance over the sample period, the D_k statistic oscillates around zero (a horizontal line when the D_k values are plotted against k). In contrast, if there are one or more sudden variance changes in the series, the D_k values drift either up or down from zero. Critical values based on the distribution of D_k under the null hypothesis of homogeneous variance provide upper and lower boundaries to detect a significant change in variance with a known level of probability. When the maximum of the absolute value of D_k is greater than the critical value, the null hypothesis of no changes is rejected. Let k^* be the value of k at which $\max_k|D_k|$ is attained. If $\max_k\sqrt{(T/2)}|D_k|$ exceeds the predetermined boundary, then k^* is taken as an estimate of the change point. The factor $\sqrt{(T/2)}$ is needed to standardize the distribution. This allows us to identify the change points.

Under the null hypothesis that the variance is homogeneous over the entire series, asymptotically D_k behaves as a Brownian bridge. The critical value of 1.36 is the 95th percentile of the asymptotic distribution of $\max_k\sqrt{(T/2)}|D_k|$. Therefore, upper and lower boundaries can be set at ±1.36 in the D_k plot. Exceeding these boundaries marks a significant change in variance in the series analyzed.

If the series under study has multiple change points, the D_k function alone is not enough because of masking effects. To avoid that problem, Inclan and Tiao (1994) designed an algorithm that uses the D_k function to systematically look for change points at different pieces of the series. The ICSS algorithm is based on successive evaluation of D_k at different parts of the series, dividing consecutively after a possible change point is found. Once the change points have been identified using the ICSS algorithm, then we move to the next step of analyzing events surrounding the periods of changes in volatility.

B. The GARCH Model

As our main objective is to identify the sudden changes in variance rather than specifically model each time series, we use a GARCH framework.[2] Bekaert and Harvey (1997a) have used a semiparametric ARCH (SPARCH) specification for six out of nineteen countries in their sample while the normal specification is used for the other thirteen countries.[3]

The GARCH (1,1) can be written as:

$$(2) \qquad Y_t = \mu + e_t, \qquad e_t \big| I_{t-1} \sim N(0, h_t), \qquad h_t = \omega + \alpha e_{t-1}^2 + \beta h_{t-1}$$

where, N represents the conditional normal density with mean 0 and variance h_t , and I_{t-1} is the information available up to time t-1. The standardized residuals of most countries' returns exhibit high kurtosis, so we use robust standard errors. Some series show evidence of autocorrelation; in those cases an AR (1) with GARCH (1,1) is estimated. The autocorrelation is more evident in daily returns than in weekly returns. Infrequent trading can be a problem in some emerging markets.

C. The Combined Model with GARCH and Sudden Changes in Variance

The GARCH model is one way of capturing the persistence of volatility observed in a time series. The model can be modified to incorporate sudden changes in the variance also. It is conceivable that a given time series would have both kinds of structure. Lastrapes (1989) and Lamoreux and Lastrapes (1990) have shown that when ARCH/GARCH models are applied to data that include sudden changes in variance then the conditional variance may be found to strongly persist over time. Hamilton and Susmel (1994) and Susmel (1997) use a switching ARCH (SWARCH) to introduce regime changes. Susmel introduces three states: low volatility, moderate volatility, and high volatility. We consider a model that combines the shifts in variance with

GARCH.[4] Our empirical approach first detects the change points by using the ICSS algorithm and then dummy variables are introduced into the variance equation of the GARCH model to account for the sudden changes in variance. The combined model with GARCH(1,1) and dummy variables is given by:

$$\text{(3)} \qquad Y_t = \mu + e_t, \qquad e_t | I_{t-1} \sim N(0, h_t) \qquad h_t = \omega + d_1 D_1 + \ldots + d_n D_n + \alpha e_{t-1}^2 + \beta h_{t-1}$$

where $D_1, \ldots, D_n$ are the dummy variables taking a value of 1 from each point of sudden change of variance onwards, 0 elsewhere.

For all the series studied, descriptive statistics were obtained, including a test for autocorrelation using the Ljung-Box Q statistic and a version of this statistic that accounts for the possibility of ARCH [Diebold (1988)]. Based on this statistic we decide whether to use an AR(1) term in the mean equation as discussed earlier. We choose GARCH as a simple yet flexible parameterization to capture those effects. The impact on the GARCH parameters of including the dummy variables in the equation is discussed in the following sections.

D. Data

The data consist of daily closing values for the Standard and Poor's 500 (U.S.), Nikkei Average (Japan), FT100 (U.K.), DAX (Germany), Hang Seng (Hong Kong), Singapore Straits Industrial (Singapore), Bolsa Indice General (Argentina), BOVESPA São Paulo Stock Exchange Index (Brazil), IGPA Index (Chile), Bombay Sensitivity Index (India), Seoul Composite Index (Korea), Kuala Lumpur Composite Index (Malaysia), IPC Index (Mexico), Manila Composite Index (Philippines), Taipei Weighted Price Index (Taiwan), and Bangkok S.E.T. Index (Thailand). Except for the Nikkei, which is price-weighted, and the BOVESPA, which is volume-weighted, the indices are value-weighted and do not include dividends.[5]

It is important to note that we follow the IFC classification of which stock markets are emerging markets. Of the emerging markets identified by the IFC, we selected the ten largest at the time of data collection. Some important markets, for example, Indonesia and China are not included because they were not in that group of the ten largest; the IFC did not list South Africa as an emerging market at the time of our data collection. The sample of ten countries represents 71.4 percent of emerging markets capitalization at the end of 1994 according to the IFC.

Our data covers the 10-year period May, 1985 - April, 1995. Most economic and market liberalization policies in these markets began in the late 1980s or early 1990s. For the analysis, the daily stock market indices are transformed into weekly rates of return based on Wednesday prices. When there was no trading on a given Wednesday, the trading day before Wednesday was used to compute the return. The analysis used daily, weekly, and monthly returns, but detailed results are reported only for weekly data. The weekly data should cause fewer problems than daily data does because of nonsynchronous trading and short term correlations due to noise. Exchange rates were obtained daily from *The Wall Street Journal*. Each country's returns were calculated in the local currency and also adjusted for U.S. dollar returns.

III. EMPIRICAL RESULTS

A. Descriptive Statistics

Table 1 presents the descriptive statistics for each series for the period 1985 to 1995, using the indices discussed earlier. The statistics - annualized arithmetic returns and standard deviations, skewness, kurtosis, the Ljung-Box Q statistic, and the number of observations are reported for weekly dollar and local returns.[6] The highest mean annualized local returns are in Brazil, at 251.5 percent, and the lowest are in Japan, at 5.3 percent; Brazil had very high inflation through most of this period. Annualized local returns for the Emerging Markets Index, at 40.1 percent, and for the Latin America Index, at 116.8 percent are much higher than the returns of 8.6 percent for the World Index and 6.6 percent for the Far East. The returns for the Far East Index are lower than those of other markets in the region because the Index is dominated by Japan. In dollar terms also the emerging markets exhibit higher returns than the developed markets, but the differences are less dramatic.

As expected, volatility is very high in emerging markets. Argentina and Brazil have the highest levels of volatility (as measured by standard deviation) in local returns, at 78.0 percent and 74.7 percent. Chile and Korea are the least volatile emerging markets during this time period, with standard deviations of 22.4 percent and 23.0 percent respectively. The U.S. and U.K. are the least volatile developed markets, with standard deviations of 14.9 percent and 16.8 percent respectively. The very high volatility in emerging markets is observed in both the local and the dollar returns. These results are consistent with those of Harvey (1995).

The distribution for most markets seems to be non-normal. Most of the developed markets have significant negative skewness. In contrast, many of the emerging markets show positive skewness. Each of the series has fat tails, as seen in the significant kurtosis, however, after the sudden changes are included in the GARCH model, the standardized residuals ($e_t/\sqrt{h_t}$) present much lower kurtosis and skewness.

B. Sudden Changes in Variance

Figure 1 presents plots of local weekly returns for each series. The dotted lines show the sudden changes detected by plotting +/- 3 standard deviations, where the standard deviation is calculated for the observations between the change points. Table 2 reports the number of sudden changes in variance as identified by the ICSS algorithm, for local and dollar weekly returns. In the weekly series, Argentina, the Philippines, U.S. and the MSCI World Index have 7 change points each; Mexico, India, Malaysia, Thailand, Hong Kong, Japan, the Emerging Markets and the Far East have 6 each; Singapore and the Latin America Index have 5 each; U.K. has 3; Brazil has 2, and Germany has only 1.[7] Results for change points in dollar-adjusted returns, as reported in Table 2, are similar in terms of the number of change points and the time period.

For each period, Table 2 also provides the level of annualized standard deviation for local and dollar weekly returns. The periods of increased volatility identified by the ICSS algorithm tend to correspond to country-specific important political and economic events as shown in the table. The changes in the level of volatility and the duration of the changes vary by country and by the type of event. Economic, political and social events cause volatility to change differently in each country. Harvey (1995) finds that country-specific factors improve the predictability of their asset pricing model. The October 1987 crash and the Gulf War were the only events that affected more than one country. The October crash resulted in very high volatility in the series for Mexico, Malaysia, Hong Kong, Singapore, U.K., U.S., the World Index, and the Far East Index. In the case of Taiwan and Thailand there were local events along with the stock market crash that caused increased volatility. The Gulf War caused periods of very high volatility in Singapore, Japan, U.S., the World Index, and the Emerging Market series, but in none of the individual emerging markets.

The most volatile period for the U.S. markets was from the week of October 14, 1987 to the week of November 4, 1987, with an annualized standard deviation of 67.9 percent. This period corresponds to the stock market crash of October 1987. Following this three-week period, the market volatility dropped to 19.3 percent. The second most volatile period started in the week beginning August 8, 1990 and lasted until the week of February 13, 1991. This period is associated with the Gulf War and had a weekly volatility of 22.7 percent.

The most volatile period in Argentina, March 8, 1989 to March 7, 1990, had a standard deviation of 146.0 percent and was associated with a period of hyperinflation during which anti-inflation programs were initiated that resulted in reducing the money supply, currency depreciation while interest payments on external debt were stopped. The second most volatile period for Argentina was around the introduction of the Austral Plan, May 1, 1985 - October 30, 1985, when the standard deviation was 110.5 percent. Inflation during this period was running at 1,000 percent, dollar deposits were frozen and the Austral Plan was put into place. In Brazil the most volatile period, November 29, 1989 - February 20, 1991, is related to several anti-inflation plans and confiscation of financial assets. In Mexico the period October 14, 1987 - April 27, 1988 also saw the implementation of anti-inflation plans to curb the almost 150 percent inflations. The stock market plunged 50 percent. These same events are reflected in the volatility of the Latin American Index.

The periods based on local returns and on dollar returns show considerable overlap. For example, in Mexico, two major shocks were identified based on both local returns and dollar returns. The largest shock for local returns was from October 1987 to April 1988 with a standard deviation of 14.22 percent. In dollar returns the period was identified from October 1987 to May 1988, with a standard deviation of 14.09 percent. The second largest shock in Mexico was from March, 1994-April, 1995 period, when the Mexican Peso collapsed and a presidential candidate was murdered.

The volatile periods in India coincide with the balance of payment crisis and the stock market scandal; in Malaysia, volatility increased when higher reserve requirements were put into place and during the period of Chinese-Malay riots; in the Philippines, the communist rebels and the Marcos-Aquino conflict are periods of very high volatility; the high trade deficit in Korea coincides with increased standard deviation during the period April 18, 1990 - January 16, 1991; in Taiwan increased volatility occurred when the Central Bank withdrew support for the currency and the crash of October 1987; during the military coup in Thailand volatility increased from 26.7 to 55.0 percent. For the Japanese market the most volatile period was April 1, 1992 - September 30, 1992, when the stock market plummeted and there was a banking crisis. These factors are reflected in the volatility of the Far East Index.

The question arises whether the volatility changes being captured are related mainly to the stock market or to volatility changes in exchange rates. A comparison of the results for local returns and those for dollar returns suggests that many of the shocks in volatility are driven by local factors other than shifts in the exchange rate regimes. As an additional analysis, we also examined sudden changes in variance in the weekly exchange rate return series. The significant changes in variance in the exchange rate series are much more numerous than those in the stock index return series for all emerging markets except for Argentina. In most cases, the periods with the greatest volatility in the exchange rate series do not overlap with the periods for either the local returns or the dollar returns. However, in certain instances, particularly in Latin America, there is overlap. For example, the 1994-1995 period in Mexico was identified as having very high volatility in all three series - dollar stock returns, local stock returns and exchange rate returns. The volatility in exchange rates appears to be affected by the exchange rate regime of the country. For example, since 1991 Argentina has had a fixed exchange rate regime so no sudden changes in variance in the exchange rate returns were detected during the period 1991-1995. These results are not reported here.

We did not directly test for the effect of stock market liberalization on volatility. However, we do split the sample into two time periods 1985-1990 and 1990-1995 and find no major changes in the overall variance or in the pattern of the sudden changes in variance. These results are consistent with the findings of Bekaert and Harvey (1997a) and De Santis and Imrohoroglu (1997). In the literature the evidence is somewhat mixed as to whether volatility increases or decreases after stock market reforms. Some countries argue that the opening of financial markets to foreign investors results in increased volatility, because of “hot money” flowing in and out easily. Bekaert and Harvey (1998) provide an excellent analysis of capital flows and liberalization. Kim and Singal (1997) also systematically examine the effects of liberalization on volatility. None of our sudden change points clearly corresponds to the initiation of market liberalization policies. We cannot say directly that liberalization does not affect volatility. However, its effect seems to be gradual and probably results in a smooth adjustment rather than a shock (see Bekaert and Harvey (1997b)). This may explain why previous attempts to measure the impact of liberalization have been mixed.

C. GARCH (1,1) Parameter Estimation and Sudden Changes in Variance

As demonstrated by Lamoreux and Lastrapes's (1990) analysis of 30 exchange-traded stocks, when regime shifts are incorporated directly into an ARCH/GARCH model, the persistence of variance indicated by the GARCH model decreases dramatically. For lack of a methodology, such as the ICSS algorithm, to detect time points of sudden variance change, their analysis divides the study period into equally spaced, nonoverlapping intervals, within which the variance might be different. By including these "shift dummies" into the GARCH model, they test the impact of sudden changes of variance on the parameters of the estimated models.

In our analysis, the sudden changes in variance detected by the ICSS algorithm can be incorporated directly into a GARCH model (1) to test the relative strengths of each type of change in variance (sudden changes versus GARCH) and (2) to analyze the impact of including the dummy variables on the persistence of variance indicated by a GARCH model alone. The first test is of importance because either model by itself may not capture all of the variance effects, i.e. there may be residual GARCH effects when a model is fitted that includes only the dummy variables, and there may still be sudden changes in the variance of standardized residuals after fitting a GARCH model. Therefore, a more complete analysis would allow for both kinds of effects. The second issue relates to the question of persistence of variance and the existence of time-varying risk premia, as raised by Poterba and Summers (1986).

The left panel of Table 3 presents the results from fitting a GARCH model alone (no sudden changes) to each of the 20 series. The right panel of Table 3 shows the results of fitting a GARCH model with dummy variables that correspond to the time points of sudden variance changes, given in Table 2 for weekly local returns. Each panel shows the estimated GARCH parameters, with their t-statistics noted in parentheses. Also included are the diagnostic statistics TR^2 and Q(16) calculated with the standardized residuals $e_t/\sqrt{h_t}$.

In sixteen of the twenty series the coefficients alpha and beta are both significant in the GARCH(1,1) only model. The remaining four series have either the alpha or the beta coefficient significant but not both. In most of the series, the sum of the GARCH coefficients is close to 1, implying extreme persistence in volatility. These results are similar to those found by De Santis and Gerard (1997). The residuals of this model continue to show sudden changes in variance for twelve of the twenty series examined as indicated by N_T in the table. When dummy variables are introduced in a GARCH(1,1) model, only two of the series have both coefficients significant. In some series, negative estimates are obtained for the parameters, so we had to impose the restriction that the GARCH coefficients be positive.

The values of the GARCH coefficients are reduced when sudden variance changes are accounted for, and most of them are no longer significant. The residuals of the combined model exhibit no further sudden changes nor significant TR^2 in all cases as expected, except Hong Kong.[8] The analysis was repeated using GARCH with a t-distribution but the results are not reported here. Even after fitting a GARCH with a t-distribution sudden changes in variance continued to exist. In this model, there were seventeen series which had both the alpha and beta coefficients significant when dummy variables for shifts in variance are not added. This model with dummies included resulted in reduced GARCH coefficients and only four series had both coefficients significant.

However, because determining the shifts in volatility is not possible ex ante, the change dummies cannot be incorporated in an ex ante model. The models of Gray (1996) and Hamilton (1988) incorporate ex ante probabilities for regime switches. The asset concentration, market development, and macroeconomic variables suggested by Bekaert and Harvey (1995) and Harvey (1995) can be used to forecast emerging market volatility.

IV. SUMMARY AND CONCLUSIONS

This study examines shifts in volatility of emerging stock market returns and the events that are associated with the increased volatility. Returns in local currency and dollar-adjusted returns are examined during the period 1985-1995. The high volatility in emerging markets is marked by several shifts. As an example, there were seven significant volatility shifts in Argentina during this time period. The annualized standard deviation was as low as 23.9 percent and as high as 146.0 percent. The large changes in volatility seem to be related to important country-specific political, social and economic events. These events include the Mexican Peso crisis, periods of hyperinflation in Latin America, the Marcos-Aquino conflict in the Philippines, and the stock market scandal in

India. The October 1987 crash is the only global event in the last decade that caused a significant jump in the volatility of several emerging stock markets.

The number of changes in variance vary from country to country. They also depend on the frequency of the data: more change points are found with daily returns than with weekly or monthly returns. Periods of high variance in local returns overlap considerably with periods of high volatility in dollar-adjusted returns.

Endnotes

1. For example see, Gray (1996), Hamilton (1988), Hamilton and Susmel (1994), and Lamoreux and Lastrapes (1990). In many studies, regime shifts are first identified and then dummy variables introduced.

2. We also repeated the analysis using GARCH with a t-distribution and find that the results are similar to the simple GARCH so we do not report the results here.

3. Bekaert and Harvey's (1997a) normal model includes asymmetries in the conditional variance process of many series.

4. All models were estimated by quasi-maximum likelihood, using the Broyden, Fletcher, Goldfarb and Shanno algorithm as implemented in RATS (Regression Analysis of Time Series) version 4.2.

5. A comparable family of indices computed by the IFC started only in 1981 and was backtracked to December 1975 by the IFC as reported in Harvey (1995). To check for consistency, we obtained the dollar returns of the IFC price index for the 1989-1993 period and found that a weekly US$ returns time series computed from our national market indexes series averages a correlation with the IFC series of 81 percent and has similar statistical properties.

6. Daily and monthly returns are not reported in the paper but can be obtained from the authors.

7. Monthly returns exhibit the least number of sudden changes in variance and daily returns the most. The aggregation of data leads to smoothing out effects, therefore monthly returns exhibit the least number of change points. The highest number of sudden changes in daily local returns is 26 for Japan, the fewest are for U.K. (7) and U.S. (10). Eight series - Brazil, Chile, Malaysia, the Philippines, South Korea, Thailand, Hong Kong, and the Far East Index - show no sudden changes in variance in the monthly local returns. For monthly returns, Argentina has the most sudden changes, 4; U.S. has 3; Mexico, India, Taiwan, U.K., and the Latin America Index have 2 each; Singapore, Germany, Japan, the MSCI World Index, and the Emerging Markets Index have 1 each.

8. We also attempt to fit the best model to each series. The criterion is to systematically fit the most parsimonious model which has insignificant TR^2 and Ljung-Box statistic. Each of the series needs dummy variables associated with the sudden changes in variance. After fitting the best possible model there are no remaining sudden changes, and none of the TR^2 or Q(16) are significant. The results can be obtained from the authors.

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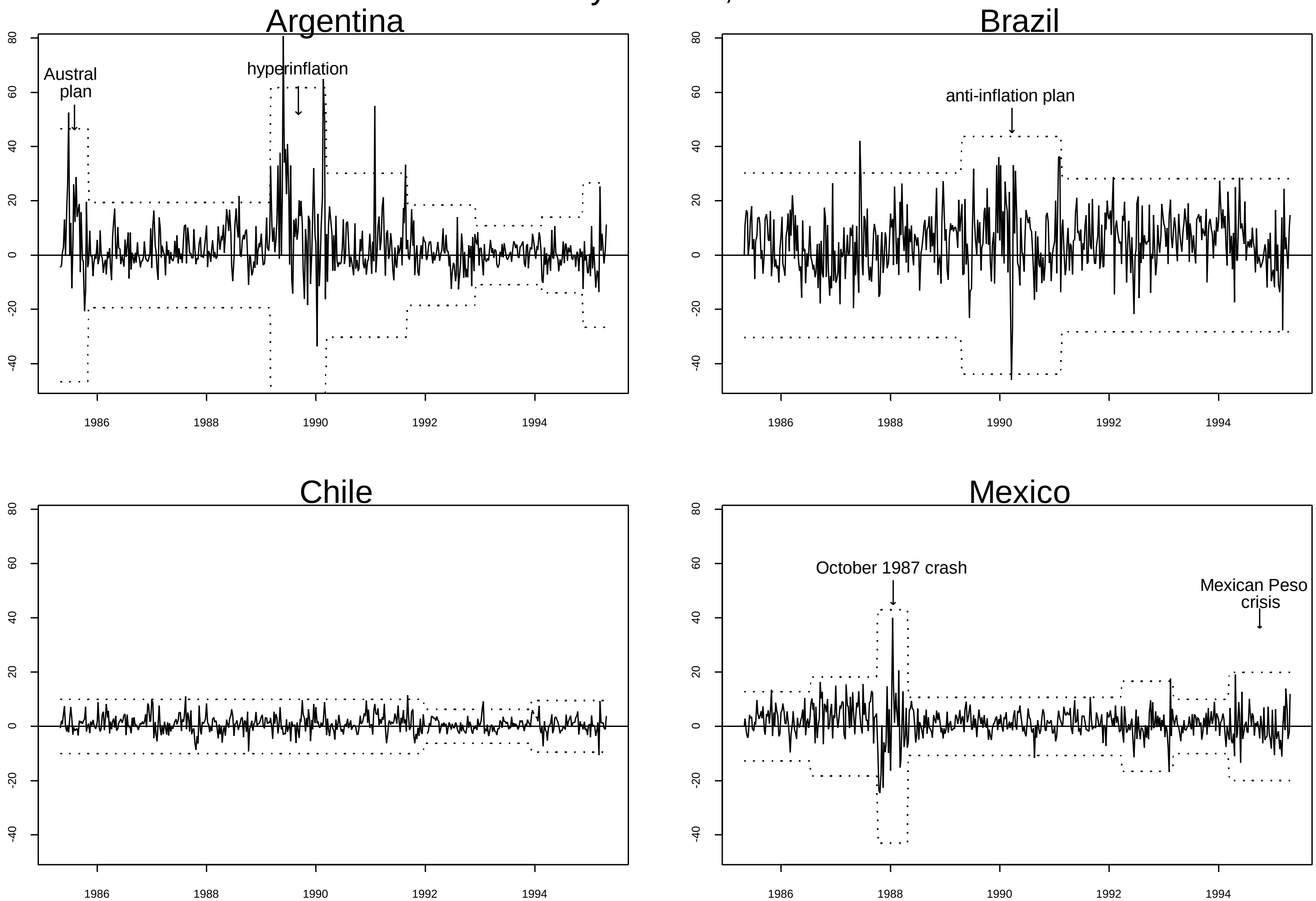
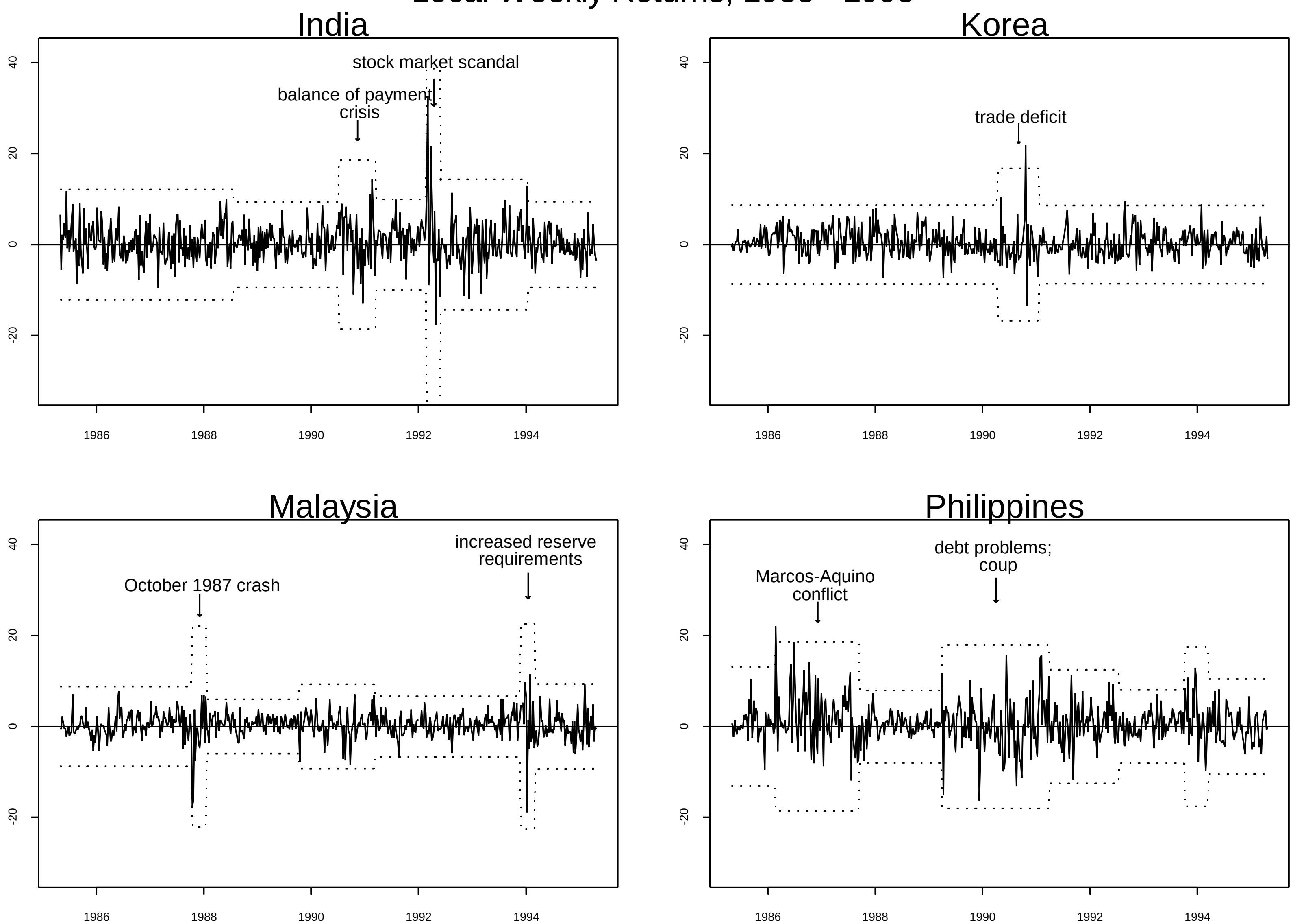
FIGURE 1
Local Weekly Returns, 1985 - 1995



dotted lines at +/- 3 standard deviations, change points estimated using the ICSS algorithm

Local Weekly Returns, 1985 - 1995



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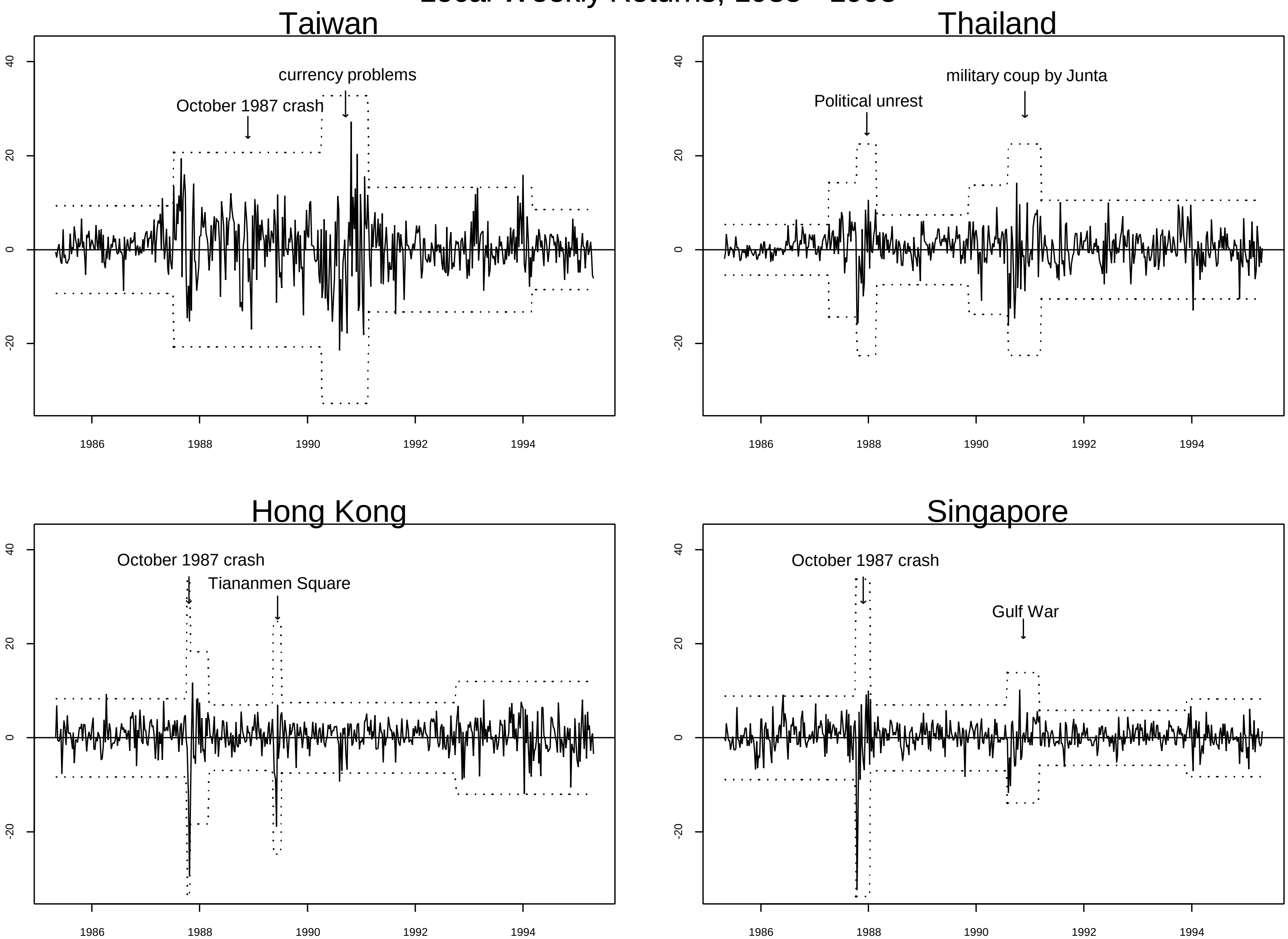
Local Weekly Returns, 1985 - 1995



dotted lines at +/- 3 standard deviations, change points estimated using the ICSS algorithm

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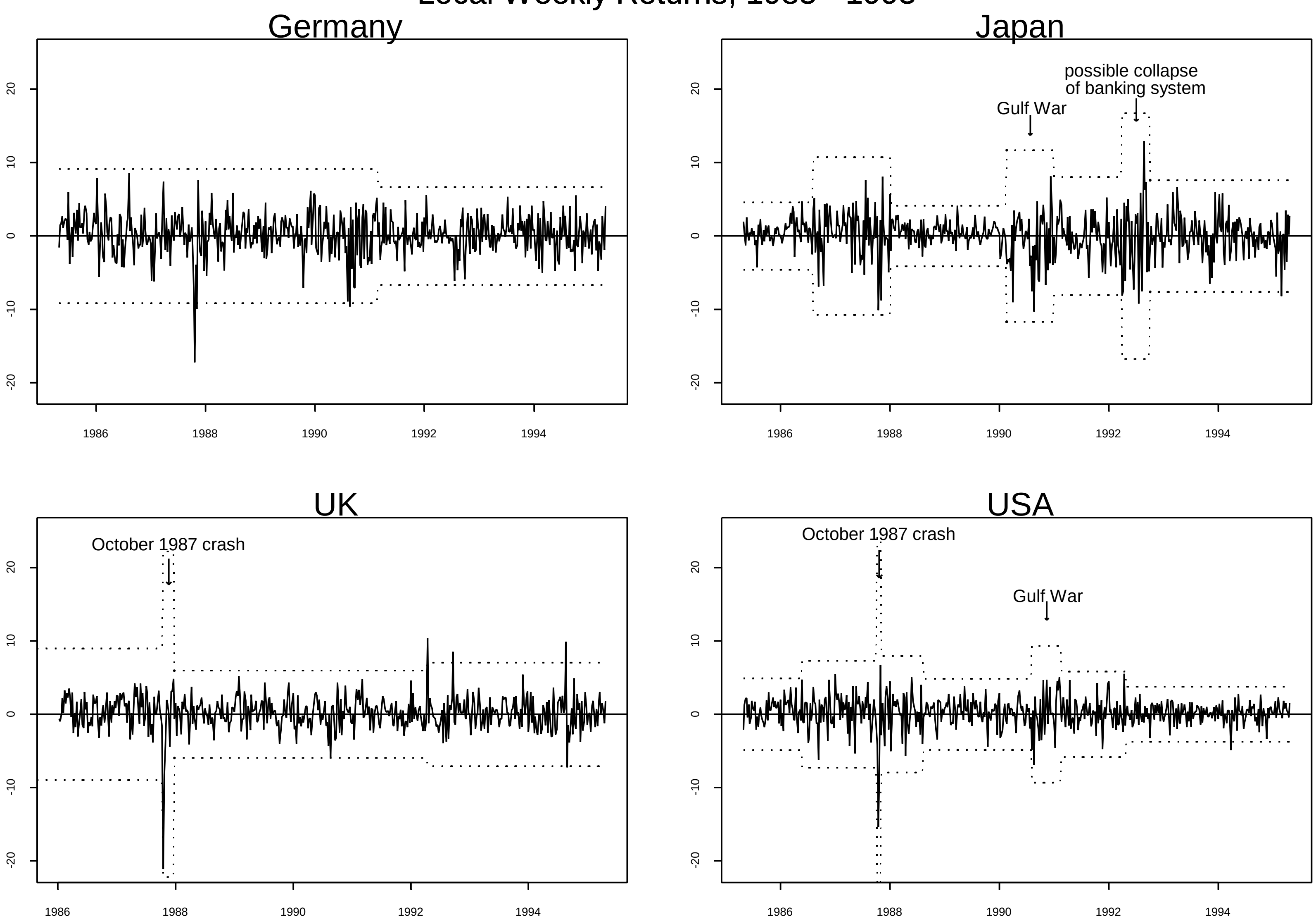
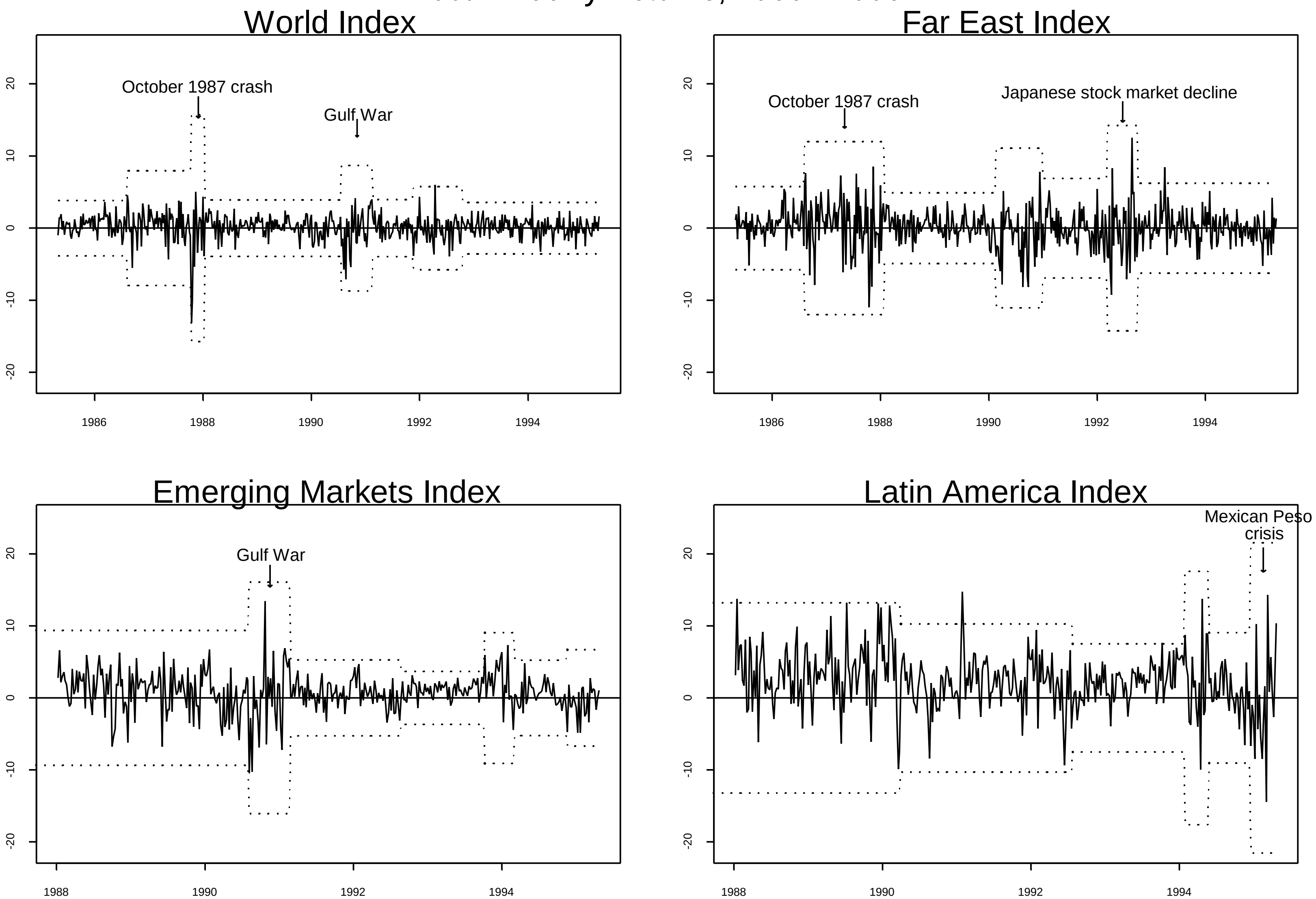


dotted lines at +/- 3 standard deviations, change points estimated using the ICSS algorithm

Local Weekly Returns, 1985 - 1995



dotted lines at +/- 3 standard deviations, change points estimated using the ICSS algorithm

TABLE 1

Descriptive Statistics for Dollar and Local Returns (May, 1985 - April, 1995)

	Dollar					Local					
	Mean	Std. Dev.	Skew	Kurt.	Q(16)	Mean	Std. Dev.	Skew.	Kurt.	Q(16)	Obs.
Latin America											
Argentina	58.1*	84.0	4.1*	46.8*	49.1*	154.6*	74.7	2.4*	11.6*	161.1*	522
Brazil	46.2*	75.4	-0.1	1.5*	13.7	251.5*	78.0	0.0	1.0*	32.6*	522
Chile	35.6*	25.2	0.1	1.6*	30.8*	44.7*	22.4	0.3*	1.1*	43.5*	522
Mexico	39.4*	46.2	-0.2	5.3*	79.6*	69.3*	42.2	0.2*	5.4*	70.2*	522
Asia											
India	18.2	33.5	0.7*	7.1*	26.6*	27.1*	32.6	0.8*	5.8*	27.5*	522
Malaysia	15.8	27.5	-1.4*	9.8*	15.3	15.6	27.2	-1.3*	9.6*	15.5	522
Philippines	31.4*	33.3	0.2*	1.8*	25.8	34.7*	33.1	0.4*	2.3*	26.3*	522
South Korea	22.7*	23.7	0.5*	3.4*	34.3*	21.3*	23.0	0.6*	4.0*	57.1*	522
Taiwan	33.5*	41.8	-0.1	2.1*	32.5*	28.8*	33.5	-0.1	2.2*	31.4*	522
Thailand	24.9*	27.2	-0.1	6.9*	7.8	23.9*	27.1	-0.6*	3.0*	32.1	522
Major Markets											
Hong Kong	20.6*	26.2	-1.7*	10.6*	29.0*	20.5*	26.1	-1.7*	10.6*	29.4*	522
Singapore	6.1	25.6	-2.3*	21.2*	25.6*	12.4	23.3	-2.3*	21.2*	28.7*	572
Germany	18.7*	21.0	-0.2*	1.3*	18.7	10.2	19.7	-0.7*	3.6*	14.0	522
Japan	17.0*	23.9	-0.2*	1.1*	9.7*	5.3	20.4	-0.4*	2.0*	24.0	522
U.K.	11.9	19.2	-1.0*	9.3*	0.6	10.3	16.8	-1.3*	15.0*	20.0	486
U.S.	11.4*	14.9	-1.2*	7.3*	33.0*	11.4*	14.9	-1.2*	7.3*	33.02*	522
Morgan Indices											
World	12.7*	13.7	-1.1*	6.0*	35.7*	8.6*	12.9	-1.4*	8.4*	29.3*	522
Emerging Markets	18.3*	19.7	-0.4*	2.2*	11.9*	40.1*	19.6	-0.4*	2.5*	53.4*	381
Far East	17.4*	23.1	0.0	1.1*	13.7*	6.6	19.9	-0.2	1.9*	23.4	522
Latin America	32.4*	29.6	-0.5*	2.4*	19.9	116.8*	29.2	-0.1	1.5	46.9*	381

The mean, standard deviation, skewness, kurtosis, and Ljung-Box statistic - Q(16) are shown for dollar and local returns for each emerging market, major market and the Morgan Stanley Indices for the regions. The mean and standard deviation have been annualized using weekly returns. Skewness, kurtosis, and Ljung-Box are reported for weekly returns. * denotes significance at 5 percent.

TABLE 2

Sudden Changes in Volatility

	# of Change Points	Period (dollar)	SD (dollar)	Period (local)	SD (local)	**Events**
Latin America						
Argentina	10/7	May 1, 85 - Oct. 23, 85	215.5	May 1, 85 - Oct. 30, 85	110.5*	• 1000% inflation; dollar deposits frozen;
		Oct. 30, 85 - Apr. 12, 89	45.9	Nov. 6, 85 - Mar. 1, 89	42.1	Austral Plan
		Apr. 19, 89 - Jul. 19, 89	258.9	Mar. 8, 89 - Mar. 7, 90	146.0*	• hyperinflation; currency collapses;
		Jul. 26, 89 - Apr. 11, 90	111.1	Mar. 14, 90 - Aug. 28, 91	75.6	interest payments stopped; elections
		Apr. 18, 90 - Oct. 16, 91	64.2	Sep. 4, 91 - Dec. 2, 92	45.6	
		Oct. 23, 90 - Jun. 17, 92	29.9	Dec. 9, 92 - Feb. 16, 94	23.9	
		Jun. 24, 92 - Dec. 23, 92	53.0	Feb. 23, 94 - Nov. 16, 94	33.0	
		Dec. 30, 92 - Jan. 26, 94	23.1	Nov. 23, 94 - Mar. 26, 95	68.8	
		Feb. 2, 94 - May 18, 94	47.0			
		May 25, 94 - Nov. 16, 94	21.3			
		Nov. 23, 94 - Apr. 26, 95	63.2			
Brazil	2/2	May 1, 85 - No. 22, 89	71.9	May 1, 85 - Apr. 19, 89	72.0	
		Nov. 29, 89 - Feb. 20, 91	110.5	Apr. 26, 89 - Feb. 13, 91	103.8*	• anti - inflation plan; deposits
		Feb. 27, 91 - Apr. 26, 95	66.1	Feb. 20, 91 - Apr. 26, 95	68.0	confiscated; new currency, presidential
						elections
Chile	3/2	May 1, 85 - Jul. 12, 89	23.5	May 1, 85 - Dec. 18, 91	24.1	
		Jul. 19, 89 - Dec. 18, 91	32.6	Dec. 25, 91 - Dec. 8, 93	14.7	
		Dec. 25, 91 - Dec. 1, 93	17.0	Dec. 15, 93 - Apr. 26, 95	23.0	
		Dec. 8, 93 - Apr. 26, 95	24.7			
Mexico	4/6			May 1, 85 - Jul. 16, 86	30.1	
		May 1, 85 - Oct. 7, 87	42.5	Jul. 23, 86 - Oct. 7, 87	43.2	
		Oct. 14, 87 - May 25, 88	101.6	Oct. 14, 87 - Apr. 27, 88	102.5*	• October 1987 crash; anti - inflation
		Jun. 1, 88 - Jan. 27, 93	26.4	May 4, 88 - Mar. 18, 92	25.0	plan; inflation at 142%; market drops
				Mar. 25, 92 - Mar. 3, 93	41.8	50%;
		Feb. 3, 93 - Dec. 14, 94	42.5	Mar. 10, 93 - Mar. 9, 94	23.7	
		De. 21, 94 - Apr. 26, 95	91.4	Mar. 16, 94 - Apr. 26, 95	49.7*	• Mexican Peso crisis and low reserves
Asia						

	# of Change Points	Period (dollar)	SD (dollar)	Period (local)	SD (local)	**Events**
India	6/6	May 1, 85 - Jul. 20, 88	30.0	May 1, 85 - Jul. 20, 88	29.1	
		Jul. 27, 88 - Jul. 4, 90	22.0	Jul. 27, 88 - Jul. 4, 90	22.1	
		Jul. 11, 90 - Mar. 13, 91	44.3	Jul. 11, 90 - Mar. 13, 91	45.1*	• balance of payment crisis; unstable
		Mar. 20, 91 - Feb. 19, 92	23.5	Mar. 20, 91 - Feb. 19, 92	22.5	govt. due to elections
		Feb. 26, 92 - May. 27, 92	103.2	Feb. 26, 92 - May 27, 92	96.3*	• stock market scandal
		Jun. 3, 92 - Jan. 12, 94	35.7	Jun. 3, 92 - Jan. 12, 94	34.8	
		Jan. 19, 94 - Apr. 26, 95	22.5	Jan. 19, 94 - Apr. 26, 95	22.6	
Malaysia	7/6	May 1, 85 - Oct. 14 , 87	18.5	May 1, 85 - Oct. 14, 87	17.7	
		Oct. 21, 87 - Nov. 11, 87	71.3	Oct. 21, 87 - Jan. 20, 88	54.7*	• October 1987 crash; Chinese - Malay
		Nov. 11, 87 - Oct. 5, 88	20.2	Jan. 27, 88 - Oct. 11, 89	12.9	riots
		Oct. 12, 88 - Oct. 11, 89	9.9	Oct. 18, 89 - Mar. 6, 91	22.4	
		Oct. 18, 89 - Mar. 6, 91	22.5	Mar. 13, 91 - Nov. 24, 93	15.9	
		Mar. 13 , 91 - Nov. 24 , 93	16.4			
		Dec. 1, 93 - Feb. 23, 94	60.5	Dec. 1, 93 - Mar. 2, 94	56.7*	• increased reserve requirements; capital
		Mar. 2, 94 - Apr. 26, 95	22.8	Mar. 9, 94 - Apr. 26, 95	22.4	control measures
Philippines	7/7	May 1, 85 - May 28, 86	25.7	May 1, 85 - Feb. 19, 86	21.7	
		Jun. 4, 86 - Oct. 21, 87	44.7	Feb. 26, 86 - Sep. 16, 87	44.9*	• Marcos - Aquino conflict; coup
		Oct. 28, 87 - Oct. 4, 89	22.8	Sep. 23, 87 - Mar. 29, 89	16.9	attempt
		Oct. 11, 89 - Mar. 27, 91	47.4	Apr. 5, 89 - Mar. 27, 91	43.1*	
		Apr. 3, 91 - Jul. 8, 92	29.4	Apr. 3, 91 - Jul. 15, 92	30.6	• debt problems; exchanges closed; coup
		Jul. 15, 92 - Oct. 27, 93	19.5	Jul. 22, 92 - Oct. 6, 93	18.2	attempt
		Nov. 3, 93 - Jun. 8, 94	40.7	Oct. 13, 93 - Mar. 16, 94	42.4	
		Jun. 15, 94 - Apr. 26, 95	23.1	Mar. 23, 94 - Apr. 26, 95	24.7	
South Korea	2/2	May 1, 85 - Apr. 11, 90	21.3	May 1, 85 - Apr. 11, 90	20.8	
		Apr. 18, 90 - Jan. 16, 91	40.9	Apr. 18, 90 - Jan. 16, 91	40.7*	• large trade deficit
		Jan. 23, 91 - Apr. 26, 95	21.8	Jan. 23, 91 - Apr. 26, 95	20.8	
Taiwan	4/4	May 1, 85 - Jul. 8, 87	21.3	May 1, 85 - Jul. 8, 87	20.7	
		Jul. 15, 87 - Apr. 4, 90	49.2	Jul. 15, 87 - Apr. 4, 90	48.5*	• October 1987 crash
		Apr. 11, 90 - Jan. 23, 91	82.4	Apr. 11, 90 - Feb. 13, 91	79.8*	• Central Bank withdraws support of
		Jan. 30, 91 - Mar. 2, 94	33.5	Feb. 20, 91 - Mar. 2, 94	32.2	currency
		Mar. 9, 94 - Apr. 26, 95	21.1	Mar. 9, 94 - Apr. 26, 95	20.5	

	# of Change Points	Period (dollar)	SD (dollar)	Period (local)	SD (local)	Events
Thailand	5/6	May 1, 85 - Jun. 17, 85	13.4	May 1, 85 - Apr. 8, 87	12.0	
				Apr. 15, 87 - Oct. 14, 87	23.4	
		Jun. 24, 85 - Feb. 24, 88	45.2	Oct. 21, 87 - Feb. 24, 88	54.7*	• President dies; political unrest; October 1987 crash; higher inflation
		Mar. 3, 88 - Nov. 8, 89	17.2	Mar. 3, 88 - Nov. 8, 89	17.4	
		Nov. 15, 89 - Aug. 1, 90	26.2	Nov. 15, 89 - Aug. 1, 90	26.7	
		Aug. 8, 90 - Mar. 13, 91	55.0	Aug. 8, 90 - Mar. 13, 91	55.0*	• military coup by Junta; corruption scandals
		Mar. 20, 91 - Apr. 26, 95	25.3	Mar. 20, 91 - Apr. 26. 95	25.0	
Major Markets						
Hong Kong	6/6	May 1, 85 - Oct. 14, 87	20.0	May 1, 85 - Oct, 14, 87	19.9	
		Oct. 21, 87 - Nov. 4, 87	71.0	Oct. 21, 87 - Nov. 4, 87	71.0*	• October 1987 crash
		Nov. 11, 87 - Mar. 2, 88	38.5	Nov. 11, 87 - Mar. 9, 88	38.9	
		Mar. 9, 88 - May. 17, 89	16.7	Mar. 16, 88 - May. 17, 89	16.7	
		May 24, 89 - Jul. 12, 89	64.0	May. 24, 89 - Jul. 12, 89	63.4*	• Turmoil in China (Tiananmen Square)
		Jul. 19, 89 - Oct, 7, 92	17.9	Jul. 19, 89 - Oct. 7, 92	17.9	
		Oct. 14, 92 - Apr. 26, 95	29.0	Oct. 14, 92 - Apr. 26, 95	28.9	
Singapore	4/5	May 1, 85 - Oct. 14, 87	24.7	May 1, 85 - Oct. 14, 87	21.4	
		Oct. 21, 87 - Jan. 20, 88	83.5	Oct. 21, 87 - Jan. 20, 88	84.2*	• October 1987 crash
		Jan. 27, 88 - Aug. 1, 90	15.9	Jan. 27, 88 - Aug. 1, 90	16.3	
		Aug. 8, 90 - Mar. 20, 91	33.9	Aug. 8, 90 - Mar. 6, 91	33.8*	• Gulf War
		Mar. 27, 91 - Apr. 26, 95	16.7	Mar. 13, 91 - Dec. 1, 93	13.9	
				Dec. 8, 93 - Apr. 26, 95	19.9	
Germany	2/1	May 1, 85 - Aug. 1, 90	21.6	May 1, 85 - Feb. 20, 91	22.0	
		Aug. 8, 90 - Apr. 24, 91	34.5	Feb. 27, 91 - Apr. 26, 95	16.0	
		May 1, 91 - Apr. 26, 95	16.2			
Japan	6/6	May 1, 85 - Jun. 17, 87	19.3	May 1, 85 - Aug. 6, 86	10.8	
		Jun. 24, 87 - Nov. 18, 87	38.3	Aug. 13, 86 - Jan. 6, 88	25.8	
		Nov. 25, 87 - Feb. 14, 90	15.1	Jan. 13, 88 - Feb. 14, 90	9.5	
		Feb. 21, 90 - Jan. 23, 91	33.6	Feb. 21, 90 - Dec. 26, 90	28.4*	• Gulf War
		Jan. 30, 91 - Mar. 25, 92	21.9	Jan. 2, 91 - Mar. 25, 92	18.2	
		Apr. 1, 92 - Sep. 30, 92	45.4	Apr. 1, 92 - Sep. 30, 92	41.0*	• stock market plummets; possible collapse of banking system
		Oct. 7, 92 - Apr. 26, 95	20.1	Oct. 7, 92 - Apr. 26, 95	18.2	

	# of Change Points	Period (dollar)	SD (dollar)	Period (local)	SD (local)	**Events**
U. K.	2/3	Jan. 8, 86 - Oct. 14, 87	19.3	Jan. 8, 86 - Oct. 14, 87	14.4	
		Oct. 21, 87 - Dec. 23, 87	56.0	Oct. 21, 87 - Dec. 23, 87	56.0*	• October 1987 crash
		Dec. 30, 87 - Apr. 26, 95	17.3	Dec. 30, 92 - Apr. 8, 92	13.4	
				Apr. 15, 92 - Apr. 26, 95	16.9	
U. S.	7/7	May 1, 85 - May 21, 86	11.1	May 1, 85 - May 21, 86	11.1	
		May 28, 86 - Oct. 7, 87	17.2	May 28, 86 - Oct. 7, 87	17.2	
		Oct. 14, 87 - Nov. 4, 87	67.9	Oct. 14, 87 - Nov. 4, 87	67.9*	• October 1987 crash
		Nov. 11, 87 - Aug. 10, 88	19.3	Nov. 11, 87 - Aug. 10, 88	19.3	
		Aug. 17, 88 - Aug. 1, 90	11.1	Aug. 17, 88 - Aug. 1, 90	11.1	
		Aug. 8, 90 - Feb. 13, 91	22.7	Aug. 8, 90 - Feb. 13, 91	22.7*	• Gulf War
		Feb. 20, 91 - Apr. 22, 92	14.1	Feb. 20, 91 - Apr. 22, 92	14.1	
		Apr. 29, 92 - Apr. 26, 95	9.0	Apr. 29, 92 - Apr. 26, 95	9.0	
<u>Morgan Indices</u>						
World	5/7	May 1, 85 - Oct. 14, 87	13.1	May 1, 85 - Aug. 6, 86	8.6	
				Aug. 13, 86 - Oct. 14, 87	14.7	
		Oct. 21, 87 - Dec. 16, 87	44.0	Oct. 21, 87 - Jan. 13, 88	38.9*	• October 1987 crash
		Dec. 23, 87 - Jul. 18, 90	10.9	Jan. 20, 88 - Jul. 18, 90	9.2	
		Jul 25, 90 - Feb. 13, 91	23.1	Jul. 25, 90 - Feb. 13, 91	21.1*	• Gulf War
		Feb. 20, 91 - Oct. 7, 91	13.4	Feb. 20, 91 - Nov. 13, 91	8.4	
		Oct. 14, 92 - Apr. 26, 95	8.9	Nov. 20, 91 - Oct. 14, 92	14.0	
				Oct. 21, 92 - Apr. 26, 95	8.6	
Emerging Markets	4/6	Jan. 20, 88 - Aug. 1, 90	21.3	Jan. 20, 88 - Aug. 1, 90	21.4	
		Aug. 8, 90 - Feb. 20, 91	39.3	Aug. 8, 90 - Feb. 20, 91	39.4*	• Gulf War
		Feb. 27, 91 - Aug. 19, 92	12.8	Feb. 27, 91 - Aug. 19, 92	12.7	
		Aug. 26, 92 - Oct. 6, 93	7.9	Aug. 26, 92 - Oct. 6, 93	7.6	
		Oct. 13, 93 - Apr. 26, 95	17.9	Oct. 13, 93 - Mar. 2, 94	22.2	
				Mar. 9, 94 - Nov. 16, 94	11.1	
				Nov. 23, 94 - Apr. 26, 95	16.4	
Far East	4/6	May. 1, 85 - Apr. 8, 87	21.3	May 1, 85 - Aug. 6, 86	13.1	
		Apr. 15, 87 - Nov. 18, 87	38.1	Aug. 13, 86 - Jan. 27, 88	29.1*	• October 1987 crash
		Nov. 25, 87 - Feb. 14, 90	15.7	Feb. 3, 88 - Feb. 14, 90	11.5	
		Feb. 21, 90 - Sep. 30, 92	28.8	Feb. 21, 90 - Dec. 26, 90	26.9	
		Oct. 7, 92 - Apr. 26, 95	17.0	Jan. 2, 91 - Mar. 4, 92	16.4	
				Mar. 11, 92 - Sep. 30, 92	34.8*	• Japanese stock market decline
				Oct. 7, 92 - Apr. 26, 95	14.9	

	# of Change Points	Period (dollar)	SD (dollar)	Period (local)	SD (local)	**Events**
Latin America	4/5	Jan. 20, 88 - Apr. 18, 90	31.2	Jan. 20, 88 - Mar. 28, 90	31.4	
		Apr. 25, 90 - Feb. 16, 94	21.6	Apr. 4, 90 - Jul. 22, 92	24.1	
				Jul. 29, 92 - Jan. 26, 94	16.9	
		Feb. 23, 94 - May 25, 94	48.7	Feb. 2, 94 - May 25, 94	45.2	
		Jun. 1, 94 - Dec. 14, 94	21.6	Jun. 1, 94 - Dec. 14, 94	20.1	
		Dec. 21, 94 - Apr. 26, 95	63.6	Dec. 21, 94 - Apr. 26, 95	54.4*	• Mexican Peso crisis

The numbers of sudden changes in variance detected by the ICSS methodology are reported for weekly returns. The numbers of change points are reported for local/dollar returns. For weekly local and for dollar returns, details are provided about each time period and the standard deviation during the period. Also included, in the last column are important political, social and economic events that took place during the periods with the highest volatility for local returns, as denoted by an *.

TABLE 3

GARCH(1,1) Parameters with and without Dummy Variables for Sudden Changes in Variance

	GARCH(1,1) Only Model					GARCH(1,1) with Dummy Variables			
Latin America	α	β	TR^2	Q(16)	N_T	α	β	TR^2	Q(16)
Argentina[a]	0.40* (3.89)	0.63* (12.50)	0.30	26.60*	2	0.10 (1.71)	0.00 (0.00)	0.00	20.50
Brazil	0.19* (2.86)	0.56* (5.23)	0.42	22.38	0	0.17* (2.30)	0.47 (1.79)	0.02	26.8*
Chile	0.11* (2.75)	0.71* (6.86)	0.30	22.21	2	0.11* (2.12)	0.00 (0.00)	0.62	20.33
Mexico	0.20* (0.06)	0.74* (11.91)	1.02	27.32*	1	0.12 (1.71)	0.25 (0.80)	0.06	22.70
Asia									
India[a]	0.18* (1.81)	0.66* (5.55)	0.07	22.45	0	0.00 (0.00)	0.00 (0.00)	2.48	16.00
Malaysia	0.14* (3.35)	0.80* (14.31)	0.05	21.20	2	0.00 (0.00)	0.03 (1.15)	0.01	22.35
Philippines[a]	0.10* (1.85)	0.86* (12.71)	1.04	11.92	3	0.00 (0.00)	0.00 (0.00)	0.00	13.40
South Korea	0.28* (2.29)	0.10 (0.30)	0.15	36.60*	0	0.14* (2.62)	0.31 (0.72)	0.27	37.70*
Taiwan	0.20* (4.83)	0.79* (20.74)	2.04	26.98	0	0.14* (3.34)	0.67* (6.68)	3.01	28.40*
Thailand[a]	0.13* (3.44)	0.84* (14.23)	0.41	19.07	0	0.00 (0.00)	0.00 (0.00)	0.05	20.30

	GARCH(1,1) Only Model					GARCH(1,1) with Dummy Variables			
	α	β	TR^2	Q(16)	N_T	α	β	TR^2	Q(16)
Major Markets									
Hong Kong	0.23*	0.56*	3.35	24.14	0	0.18	0.28	6.34*	22.45
	(6.60)	(25.73)				(1.83)	(1.11)		
Singapore	0.14*	0.80*	0.03	17.75	2	0.06	0.00	0.00	13.30
	(2.50)	(25.70)				(1.44)	(0.00)		
Germany	0.13	0.65*	2.15	15.56	1	0.11	0.62*	1.05	15.60
	(1.46)	(2.52)				(1.20)	(1.96)		
Japan	0.19*	0.79*	0.77	21.97	0	0.12*	0.63*	0.18	18.20
	(4.87)	(20.40)				(2.99)	(4.93)		
U.K.[a]	0.05*	0.11	0.10	14.50	3	0.02	0.00	0.16	14.60
	(2.10)	(1.38)				(0.27)	(0.00)		
U.S.[a]	0.09	0.89*	2.29	29.90*	2	0.00	0.00	0.59	26.3
	(1.50)	(17.00)				(0.00)	(0.00)		
Morgan Indices									
World[a]	0.10*	0.88*	0.98	22.42	1	0.03	0.00	0.07	20.2
	(3.51)	(21.42)				(0.55)	(0.00)		
Emerging Markets[a]	0.18*	0.81*	0.00	57.01*	0	0.08	0.00	0.45	46.20*
	(3.31)	(15.96)				(1.15)	(0.00)		
Far East[a]	0.20*	0.73*	0.21	21.28	1	0.07	0.00	0.05	15.20
	(3.81)	(9.82)				(1.66)	(0.00)		
Latin America[a]	0.24*	0.66*	0.00	24.65*	3	0.20*	0.00	0.01	27.50*
	(3.99)	(8.30)				(2.14)	(0.00)		

After detecting points of sudden change in variance for weekly local data, using the ICSS algorithm, dummy variables are introduced in the variance equation:

Mean Equation: $Y_t = \mu + e_t$ or $Y_t = \mu + \varphi_1 Y_{t-1} + e_t$, where $e_t|I_{t-1} \sim N(0,h_t)$ and h_t is given by the variance equation.
Variance Equation: $h_t = \omega + d_1 D_1 + ... + d_n D_n + \alpha e_{t-1}^2 + \beta h_{t-1}$

where $D_1,...,D_n$ are the dummy variables, D_i=1 for t= κ_i, κ_{i+1}, ...T. t-statistics are in parenthesis. N_T is the number of sudden changes in variance remaining after fitting a GARCH(1,1).

* denotes significance at 5 percent.
[a] These series had negative estimates of the parameters when unconstrained maximization was used in the model GARCH (1,1) with sudden changes, so we had to impose the restriction that the GARCH parameters be positive.