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Stock Returns and Volatility in Emerging Financial Markets

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Abstract

In this paper we study the dynamic behavior of stock returns and volatility in emerging financial markets. In particular, we focus our attention on the following questions:

- Does stock return volatility in emerging markets change over time? If so, are volatility changes predictable?
- How frequent are *big surprises* in emerging stock markets?
- Is there any relationship between market risk and expected returns?
- Has liberalization affected return volatility in emerging financial markets?

Our findings can be summarized as follows. First, there is strong evidence of predictable time-varying volatility in almost all countries. In general, changes in volatility are highly persistent. Second, a fat-tailed distribution improves the fitting ability of the model. Third, investors are not rewarded for market-wide risk. Finally, we do not find any systematic effect of liberalization on stock market volatility.

1. Introduction

The flow of portfolio investments to emerging financial markets[1] has increased from $6.2 billion in 1987 to $37.2 billion in 1992 (Gooptu [1993]). Although debt instruments (bonds, certificates of deposit and commercial paper) are still the main component of such flows, foreign investors have shown an increasing interest in equities from developing countries. Claessens and Gooptu [1993] estimate that the flow of foreign capital to equity almost doubled from $7.6 billion in 1991 to $13.1 billion in 1992.

The revival of emerging financial markets, after the debt crisis of the early Eighties, represents a new challenge for researchers. Probably the most commonly known characteristic of these markets is their high volatility compared to more developed markets. However, statements about volatility are often based on estimates of the variance of asset returns over relatively long periods of time and, therefore, are of little use to investors who have to make periodic decisions on portfolio allocation. The purpose of this study is to characterize the dynamic behavior of stock returns and volatility in a large number of emerging markets. In particular, we focus our attention on the following questions:

- Does stock return volatility change over time? If so, are volatility changes predictable?
- How frequent are *big surprises* in emerging stock markets?
- Is there any relationship between market risk and expected returns?
- Has liberalization of emerging financial markets affected return volatility?

The importance of models of time-varying volatility in finance has been widely documented in recent years. In particular, the Autoregressive Conditional Heteroskedasticity (ARCH) process proposed by Engle [1982] and many of its generalizations have been successfully applied to traditional models of asset pricing, problems of optimal portfolio choice, strategies of dynamic hedging and pricing of derivative securities (see Bollerslev, Chou and Kroner [1992] for an extensive overview). Most applications, however, are limited to the study of U.S. markets

[1]The term emerging market reflects the association of the market with a low-or-middle-income economy as defined by the World Bank. See the International Finance Corporation Index Methodology [1993] for a more detailed description of the characteristics of these markets.

or, at most, of a limited number of developed international markets. Given the success of ARCH models especially in applications to high frequency financial data, we use them to answer the questions addressed in the paper.

We proceed in several steps. First, we choose a GARCH(1,1) process with an autoregressive component in the mean equation as our benchmark model to test whether volatility changes are predictable. Second, we compare different conditional distributions to obtain the model that best fits the kurtosis in the data. Third, we test the hypothesis that emerging markets display a positive risk-premium using a GARCH in Mean (GARCH-M) model. Finally, we test the hypothesis of a structural change in the conditional variance equation due to market liberalization.

Our findings can be summarized as follows.

First, we find strong evidence of time-varying volatility. From a qualitative point of view, our results resemble those of many studies on developed markets: periods of high/low volatility tend to cluster and volatility shows high persistence. However, from a quantitative point of view, volatility is considerably higher in emerging markets.

Second, the use of a fat-tailed distribution instead of a normal density improves the goodness of fit of our model, thus supporting the idea that *big surprises* are often observed in these markets.

Third, we do not find any relationship between expected returns and different measures of market risk. This evidence contradicts the prediction of most asset pricing models. However, some evidence consistent with our findings exists also for several developed markets.

Finally, in most cases, we do not find any evidence of a systematic effect of market liberalization on stock return volatility.

The paper is organized as follows. Section 2 contains a description of the models of expected stock return and volatility used in the paper. Section 3 describes the data. Section 4 contains a discussion of the empirical evidence. Section 5 concludes the paper.

2. Empirical Methods

Many empirical studies of financial time series have successfully used the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) process of Bollerslev [1986] to model the behavior of the conditional variance over time. One of the most appealing properties of GARCH models is their ability to accommodate volatility clustering. This phenomenon is often observed in speculative price changes, especially in high frequency data (for an early discussion see Mandelbrot [1963]).

In the following subsections, we discuss several models that describe the behavior of stock returns in emerging financial markets and we specify the hypotheses to be tested. A common feature of all the models is the use of a GARCH process for the conditional variance.

2.1. The Basic Model: AR(1)-GARCH(1,1)

Let R_t denote the return on a market index at time t. The first model that we consider assumes a simple AR(1) process for R_t, with a conditional normal distribution,

$$R_t = a + bR_{t-1} + u_t \qquad u_t|I_{t-1} \sim N(0, h_t) \tag{2.1}$$

where

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}. \tag{2.2}$$

The bR_{t-1} component is included in the mean equation to take into account the autocorrelation induced by nonsynchronous trading in the assets that make up a market index. The reason why infrequent trading in some securities can induce autocorrelation in a market-wide index is easily explained with an example. Consider two securities A and B such that B trades less frequently than A. When market-wide news become available the price of security A reacts faster than that of security B. The lagged reaction of the price of B generates a (spurious) positive serial correlation between the returns on the two securities. If the securities are included in the same index, the serial cross-correlation will generate autocorrelation in the index. The parameterization that we use to account for the effect of nonsynchronous trading follows the approach of Lo and MacKinley [1988] and Nelson [1991]. An alternative approach, proposed by Scholes and Williams [1977], models index returns as an MA(1) process. As pointed out by Nelson [1991], there is little difference between the two approaches if the AR coefficient is small and the autocorrelations at lag one are equal.

The GARCH(1,1) parameterization for the conditional variance implies that current volatility depends on past squared innovations and an autoregressive component. Although this specification is not as general as the GARCH(p,q) model proposed by Bollerslev [1986], most empirical applications find that a parsimonious parameterization is sufficient to model the conditional variance. Since equation (2.2) defines a variance, a nonnegativity restriction has to be imposed on both α and β. Moreover, Bollerslev [1986] shows that the sum $(\alpha + \beta)$ has to be smaller than 1.0 for the volatility process to be stationary.

The suggested parameterization of the model is extremely simple. In particular, the mean equation only contains an autoregressive component to explain market index returns. However, since the focus of the paper is mainly on volatility, a possible misspecification of the mean equation is not of great concern, because the conditional variance estimates obtained from a GARCH model are robust to an incorrect specification of the conditional mean (Nelson [1992]).

Under the assumption of conditional normality, the parameters of the AR(1)-GARCH(1,1) model are estimated using maximum likelihood. Since the likelihood function is nonlinear in the parameters, an iterative procedure is needed to find a maximum. In this application we use the BFGS (Broyden, Fletcher, Goldfarb and Shanno) algorithm along with numerical derivatives of the likelihood function.

We use the basic model to address two questions. First, does volatility in emerging financial markets change over time? Second, are volatility changes predictable?

2.2. Non-normal Conditional Distribution

Besides their ability to accommodate volatility clustering, gaussian GARCH models have an additional feature: the implied unconditional distribution is leptokurtic (Bollerslev [1986]). This property is particularly appealing in the analysis of high frequency financial data since strong evidence exists that the empirical distribution of asset returns has fatter tails than the normal density function (see, among others, Fama [1965], Fama and Roll [1971], Harris [1986]). Unfortunately, a large body of evidence from the GARCH literature shows that a gaussian GARCH process is not sufficient to account for all the leptokurtosis in the data (see, for example, Bollerslev [1987]). This limitation is easily detected by computing the (estimated) standardized residuals $\hat{z}_t = \hat{u}_t \hat{h}_t^{-1/2}$ from the model and showing that their distribution is leptokurtic.

The large number of *very high* and *very low* returns observed in emerging markets suggests that leptokurtosis might be an even more relevant issue in this case. In many studies, the Student$-t$ distribution is considered as an alternative to the normal. However, when the empirical distribution of asset returns has very fat tails, the fourth moment of the $t-$distribution may fail to exist. For this reason, we use an alternative parameterization of the conditional distribution which overcomes this problem. In particular, we estimate the model assuming a Generalized Error Distribution (GED)[2]

$$f(u_t) = \frac{v \exp\left[-(1/2)|u_t h_t^{-1/2}/\lambda|^v\right]}{\lambda\, 2^{[(v+1)/v]}\, \Gamma(1/v)} h_t^{-1/2}$$

where $\Gamma(\cdot)$ is the gamma function, v is a measure of thickness of the tails of the distribution and λ is a constant

$$\lambda = \left[\frac{2^{(-2/v)}\,\Gamma(1/v)}{\Gamma(3/v)}\right]^{1/2}.$$

For $v = 2$ the GED distribution coincides with the normal, for $v < 2$ it has thicker tails than the normal and, for $v > 2$, it has thinner tails than the normal. The kurtosis for the GED distribution is equal to

$$\kappa = \frac{\Gamma[\frac{5}{2}(1+\beta)]\,\Gamma[\frac{1}{2}(1+\beta)]}{\left\{\Gamma[\frac{3}{2}(1+\beta)]\right\}^2}$$

where $\beta = (2-v)/v$.

Also in this case estimation is performed using maximum likelihood.

2.3. Expected Returns and Market Risk

The model discussed in the previous sections uses lagged returns as the only explanatory variable in the mean equation. However, many models of asset pricing relate expected asset returns to some measure of risk. For example, according to the Capital Asset Pricing Model (Sharpe [1964], Lintner [1965] and Black [1972]), the expected return on any asset is a linear function of the covariance between the return on that asset and the return on the market portfolio. This implies that the expected return on the market portfolio is a linear function of its own variance.

More generally, other authors have argued that alternative measures of risk should be used to explain expected returns (see, for example, Kraus and Litzenberger [1976]).

The ARCH in Mean (ARCH-M) model of Engle, Lilien and Robins [1987] can be used to explicitly parameterize the conditional expectation of asset returns as

[2]See Box and Tiao [1973] for a theoretical discussion of the Generalized Error Distribution and Nelson [1991] for an application to financial data.

a function of volatility. In particular, the AR(1)-GARCH(1,1) model of section 2.2 can be generalized as follows

$$R_t = a + bR_{t-1} + ch_t^p + u_t \qquad u_t|I_{t-1} \sim GED(0, h_t) \tag{2.3}$$

where $p = 0.5, 1$ and

$$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}. \tag{2.4}$$

If expected returns increase with risk, the c coefficient in equation (2.3) must be positive.

Slightly different parameterizations of the model have been used by French, Schwert and Stambaugh [1987] and Baillie and De Gennaro [1990] to study the relation between expected returns and volatility in the U.S. market.

2.4. Liberalization and Return Volatility

The liberalization of international financial markets is a relatively new phenomenon. For example, many barriers to international investment were lifted in Japan and the United Kingdom only at the beginning of the Eighties. The process of liberalization started even later in many emerging markets (see Table A1 for a description of the legal organization of the markets included in this study). This fact may appear surprising in light of the need for foreign capital in most developing countries. However, one of the arguments often used against liberalization is that investment flows towards emerging markets would be extremely volatile in response to changing economic conditions. One of the consequences of volatile investment flows would be high volatility in stock prices (see, for example Kim and Singal [1993]). Based on this argument, one should expect the estimated volatility to increase after the liberalization date.

The hypothesis of a change in volatility due to market liberalization can be easily tested. Under the assumption that the conditional volatility process is strictly stationary (i.e. $\alpha + \beta < 1$) equation (2.2) implies that the unconditional variance of u_t is equal to $\frac{\omega}{1-\alpha-\beta}$. To test the hypothesis that the unconditional variance of stock returns changes with liberalization, we reparameterize equation (2.2) as follows

$$h_t = \omega + \delta d_t + \alpha u_{t-1}^2 + \beta h_{t-1} \tag{2.5}$$

where d_t is a dummy variable which is equal to 0 before the liberalization date and 1 afterwards. If volatility increases with liberalization the parameter δ should be significantly positive.

3. Data

The main source of data for this study is the Emerging Markets Data Base (EMDB) constructed by the International Finance Corporation (IFC). This data base contains monthly and weekly stock market indexes for a large number of developing countries. These indexes have the advantage of being consistently computed across different countries and, therefore, directly comparable. The stocks included in the indexes are selected on the basis of market size, trading activity and sector representation. The IFC also provides an index that includes dividend payments so that return series can be computed for all the emerging markets which include capital gains and dividend yields. All indexes are weighted by market capitalization.

The IFC indexes are computed in local currency as well as in U.S. dollars. For most markets, the IFC uses exchange rates from the Wall Street Journal or the Financial Times for the conversion into dollars. If multiple exchange rate systems exist, the IFC chooses the rate that applies to the repatriation of capital. In this study, we analyze both U.S. dollar and local currency returns. The dollar returns are relevant for U.S. investors who are interested in diversifying their portfolio at the international level. However, since they are converted into dollars using the spot exchange rate at each point in time, they reflect the return from an investment which is not hedged against currency risk. The returns measured in local currencies can be interpreted as the relevant returns for local residents or, alternatively, as an approximation of the return from a fully hedged portfolio for U.S. investors.[3]

We use the weekly series for our study. All the index series cover the period from the last week of December 1988 to the first week of May 1994 for a total of 279 observations in terms of returns.[4] The countries for which the IFC indexes are available can be grouped in different geographical regions:

- Europe/Mideast: Greece, Jordan, Portugal, Turkey.
- Asia: India, Korea, Malaysia, Pakistan, Philippines, Taiwan/China, Thailand.
- Latin America: Argentina, Brazil, Chile, Colombia, Mexico, Venezuela.

[3] In practice, however, the number of financial instruments available to cover the exposure to currency risk is extremely limited for most emerging markets.

[4] The only exception is Pakistan for which the weekly index is only available from the last week of March 1991.

We also study three regional indexes (measured in U.S. dollars): Composite, Asia and Latin America.

Most of the countries included in the EMDB data set use a Monday-Friday trading week. The only exceptions are Jordan, Korea, Pakistan and Taiwan/China.

In order to have a benchmark for our results, we extend our analysis to weekly return series from four developed markets: U.S.A., Germany, Japan and the United Kingdom. The data for these markets are computed from the daily Financial Times Actuaries World Indices (FTAWI). Also in this case, the indexes can be used to construct weekly returns which include both dividend yields and capital gains. The indexes are constructed following two criteria: investibility and market representation. In particular, stocks which are available to foreign investors are included in the index in descending order of size. The selection continues until the sample included in the index represents approximately 85% of the capitalization of the investible sample. For consistency with the emerging market data, we assume a Monday-Friday trading week to compute the returns.

Tables 1a and 1b contain summary statistics for the weekly returns measured in local currency and U.S. dollars respectively. Emerging markets are characterized by a higher volatility than developed markets. The most extreme case is Argentina for which the volatility of weekly returns (in local currency) is equal to 14.2%; the corresponding measure for the U.S. market is 1.66%. In most cases, higher average returns appear to compensate investors for a higher level of risk. For example, the average weekly return is equal to 3.97% for Argentina and 0.25% for the U.S. Average returns from emerging markets are usually lower when converted into U.S. dollars. However, table 1b confirms the qualitative results of table 1a: developing markets are more volatile and often provide higher average returns. Another interesting characteristic of the majority of the emerging markets is the high measure of kurtosis; this suggests that *big surprises*, of either sign, are observed more often than in developed markets.

4. Empirical Results

4.1. Time-Variation and Predictability in Volatility

The first issue addressed in this study is whether volatility in emerging markets changes over time in a predictable fashion. Table 2 contains the results of a battery of tests used to answer this question.

We estimate two models in which returns follow an AR(1) process. However, in model a, we also assume a constant conditional variance, whereas in model b, we assume that the conditional variance follows a GARCH(1,1) process. For each model, we estimate the standardized residuals ($\hat{z}_t = \hat{u}_t \hat{h}_t^{-1/2}$) and the squared standardized residuals and then, for each series, we compute the Ljung-Box portmanteau statistic to test the null hypothesis of no autocorrelation up to order 10. The results of this test strongly support the AR(1)-GARCH(1,1) parameterization.

Consider first the returns measured in local currencies. In 12 out of 17 cases the squared standardized residuals obtained from model a show some form of autocorrelation. In all instances, the autocorrelation disappears when the conditional variance is assumed to follow a GARCH process. Similar results are obtained for the U.S. dollar returns; model a displays autocorrelation in the squared standardized residuals for 16 out of 20 indexes. In all the 16 cases the GARCH parameterization successfully removes the autocorrelation.

To further evaluate the predictability of time-varying volatility, we also report the p-values for the likelihood ratio test of the hypothesis that the coefficients α and β in the GARCH parameterization are jointly different from zero. The results confirm the findings of the portmanteau test. Namely, the GARCH parameters are significantly different from zero whenever model b helps eliminate the autocorrelation in the squared residuals.[5] This result holds whether returns are measured in local currency or U.S. dollars.

To complete the diagnostics of the AR(1)-GARCH(1,1) parameterization we also compute the Ljung-Box portmanteau statistic for the standardized residuals. The purpose of this test is to evaluate whether any form of autocorrelation is left in the return series after the AR(1) correction for nonsynchronous trading. The results are again supportive of the proposed parameterization. When returns are computed in local currencies, we detect a residual autocorrelation only for Pakistan out of the 17 indexes. The null hypothesis of no autocorrelation is rejected in 5 out of 20 cases when returns are measured in U.S. dollars.

To summarize, the results of Table 2 confirm that volatility in emerging financial markets changes over time and, in particular, a GARCH(1,1) process can be successfully used to predict the future behavior of market volatility. These findings are consistent with the evidence obtained from developed markets. We

[5]The only exception is Portugal for which the GARCH coefficients are significantly different from zero even though the model with constant conditional variance does not display any autocorrelation in the squared residuals.

provide the results of the same tests for four large developed markets (U.S.A., Germany, Japan, and U.K.) in panel A of Tables A2a and A2b. In particular, we find evidence of a GARCH process in the conditional variance for all indexes with the exception of the Japanese returns measured in U.S. dollars.

4.2. Non-normal Conditional Distributions

There is a wide body of evidence against conditional normality of returns in financial markets of developed countries. Since the empirical distributions of returns in emerging financial markets display a large number of *extreme* observations, it seems natural to question the conditional normality assumption in our model. In order to address this issue, we estimate two versions of the AR(1)-GARCH(1,1) model; the first version assumes conditional normality whereas the second version assumes a conditional Generalized Error Distribution.[6] In our estimation we treat as an outlier any return that is larger (in absolute value) than three times the sample standard deviation. This assumption may weaken the empirical evidence against the normality assumption. However, we want to rule out the possibility that our results are driven by few extreme values in the return series.

In Table 3, we report the sample kurtosis and the theoretical kurtosis from the two models. For the model that assumes conditional normality, the sample kurtosis of the estimated residuals is always larger than its theoretical value of 3.0, with the only exception of Pakistan (local currency and U.S. dollars) and Asia (U.S. dollars). Despite the use of a dummy to reduce the effect of outliers, in many instances the sample kurtosis is more than two standard errors above 3.0.[7] When we use a GED distribution the (estimated) theoretical kurtosis is always larger than 3.0 and closer to the sample kurtosis of the residuals. To determine whether the estimated GED distribution is statistically different from a normal distribution, we test the null hypothesis that the tail-thickness parameter ν is equal to 2.0 against the one-sided alternative that ν is less than 2.0. In many cases the parameter is significantly smaller than 2.0, at least at the 10% level, which implies a conditional distribution with fatter tails than the normal.

Once again, these results are consistent with the findings for the four developed markets included in our data set. From panel A of Tables A2a and A2b,

[6]We also estimated an additional version of the model using a Student-t distribution and obtained similar estimates. However, as discussed in Section 2, we prefer the GED parameterization as an alternative to the normal because of its statistical properties.

[7]The asymptotic standard error for the estimated kurtosis is $\sqrt{24/T}$ where $T = 279$ is the sample size.

it is evident that the estimated residuals display a higher kurtosis than can be accommodated by the normal distribution. Therefore, a GED parameterization improves the fitting ability of the model.

4.2.1. The Selected Model of Conditional Volatility

Based on the results discussed in the previous subsections we choose the AR(1)-GARCH(1,1) parameterization with a conditional GED distribution as the benchmark model to predict conditional volatility and to answer the other questions addressed in the paper. Tables 4a and 4b contain the parameter estimates for the benchmark model when returns are computed in local currencies and U.S. dollars respectively. The results are consistent with the findings of other empirical work on time-varying volatility: the GARCH parameterization is statistically significant in most cases; the β coefficient in the conditional variance equation is considerably larger than α and the conditional variance generally shows high persistence (measured by $\alpha + \beta$).

As mentioned in section 2.1, the sum $(\alpha + \beta)$ must be less than unity for the conditional volatility process to be stationary. Although we do not compute a formal test of the null hypothesis that this sum equals unity against the alternative that it is less than one, a careful look at the magnitudes of the estimated coefficients relative to their standard errors indicates that, for most of the countries, the process is in fact stationary. However, in some cases (e.g. Argentina and Colombia), the conditional variance process is close to being nonstationary, at least based on point estimates. Although the detection of Integrated-GARCH (IGARCH) processes in financial time series is not unusual, a model of conditional volatility that is not stationary is of limited use to investors. We believe that a deeper analysis of these markets might be of some help to solve this problem. Alternatively, a Fractionally Integrated GARCH (FIGARCH) parameterization (Baillie, Bollerslev and Mikkelsen [1994]) could be used. We leave these generalizations to future extensions of this study.

Panel B in Tables A2a and A2b confirm that time-varying conditional volatility, with clustering and high persistence, is also detected in developed financial markets. In particular, strong evidence of a GARCH process in variance is found when returns are measured in local currencies. In the case of U.S. dollar returns, the results are reversed for Japan and U.K.

4.3. Expected Returns and Volatility

It is well established that emerging markets are more volatile than most developed financial markets. This evidence raises the question whether investors in these markets are compensated for undertaking a higher level of risk. Given the successful performance of the GARCH model analyzed in the previous sections, we address this question using two versions of a GARCH-M model. The first parameterization uses the conditional variance as a potential explanatory variable for expected returns. The second parameterization replaces the conditional variance with the conditional standard deviation. In both cases a conditional GED distribution is assumed. Maximum likelihood estimates are computed for the two models using weekly returns in local currencies and in U.S. dollars.

The results for the models that use returns in local currencies are reported in Tables 5a (variance in mean) and 6a (standard deviation in mean). In general, we find no evidence of a positive and significant reward-to-risk relationship.The point estimates of the c coefficient, which links expected returns to market volatility, are mostly small in magnitude and vary in sign across countries. In Table 5a the coefficient c is significantly different from zero for only 2 of the 17 countries in our sample and only once (Argentina) at the 1% level. Furthermore, although statistically significant, the estimate of c is very small for Argentina and has a negative sign for Brazil. The estimates of the other parameters are very similar to their counterparts in Table 4a. The results are essentially unaffected when the conditional standard deviation is used instead of the conditional variance as a measure of market risk. The main change is that, in this case, none of the estimated c coefficients is statistically significant at any reasonable level.

The results of the corresponding estimates for U.S. dollar returns are reported in Tables 5b and 6b. The results support our findings in the case of local currencies. No significant relationship is detected between expected returns and conditional variance or conditional standard deviation.

The results discussed above might seem surprising in light of one of the most widely accepted predictions of asset pricing theory. However, several studies find similar results for the U.S. market (see, for example, Baillie and De Gennaro [1990] and Nelson [1991]). To further confirm this evidence, we estimate the GARCH-M model for U.S.A., Germany, Japan and U.K. The results are reported in panels C and D of Tables A2a and A2b. Only in one instance (German returns measured in U.S. dollars) we find evidence of a positive relationship between expected returns and standard deviation which is statistically significant.

The two measures of risk proposed above have one characteristic in common:

they both assume that country specific risk should be priced. Of course, this implies that, in our analysis, financial markets are assumed to be perfectly segmented. If this assumption is incorrect, alternative measures of risk should be used. For example, if markets are perfectly integrated and an international version of the Capital Asset Pricing Model holds, then the correct measure of market risk is the covariance of each index return with the return on a world-wide portfolio (for a survey on international asset pricing models see Stulz [1994]). On the other hand, if the degree of international integration changes over time, several measures of market risk might be relevant in explaining asset returns (see Bekaert and Harvey [1994]).

4.4. Market Liberalization and Stock Return Volatility

The last issue addressed in this study is whether the opening of emerging financial markets to foreign investors has affected return volatility. As discussed in section 2.4, one of the arguments often used against market liberalization is that investment flows from developed markets are very sensitive to changing economic conditions in developing countries; as a consequence, one would expect higher volatility after the opening date.

Given the relatively short time span covered by the IFC data set and the recent phenomenon of international liberalization for most emerging markets, we are able to compute a test of volatility change only for a subset of developing countries: Turkey, India, Korea, Philippines, Taiwan, Argentina, Brazil, Colombia, Mexico and Venezuela.

The results are reported in Table 7. We test the hypothesis that the unconditional variance of the estimated model is equal to $\frac{\omega}{1-\alpha-\beta}$ before market liberalization and to $\frac{\omega+\delta}{1-\alpha-\beta}$ after the opening date.[8] The table reports the point estimates for the unconditional variance and the p-values for likelihood ratio test that the variance changes after the liberalization. The point estimates of the δ coefficient vary considerably both in size and sign across countries so that we do not detect a systematic relation between $\frac{\omega}{1-\alpha-\beta}$ and $\frac{\omega+\delta}{1-\alpha-\beta}$. Moreover, in most cases the change is not statistically significant. Venezuela (local currency) and Colombia (local currency and U.S. dollars) are the only countries for which the hypothesis of a positive change in volatility cannot be rejected at least at the 10% level. A

[8]We also tried an alternative test in which all the parameters of the conditional variance equation are allowed to change with liberalization. However, estimation in this case is often harder and the quality of the results are consistent with those reported in Table 7.

significant change is also detected for Argentina (local currency and U.S. dollars) at the 10% level. However, in this case the volatility decreases after liberalization. To reinforce our findings, we also include plots of the estimated conditional variance for some of the countries included in our data set. Three Asian countries (India, Korea and Taiwan) are included in Fig. 1a and three Latin American countries (Argentina, Brazil and Colombia) are included in Fig. 1b. It is evident from the plots that the effect of liberalization on volatility largely differs across countries. In summary, we find consistent empirical evidence against the hypothesis of increased volatility driven by market liberalization.

It should be pointed out that additional factors, not directly analyzed in this study, may affect the behavior of volatility over time. First, the number of traded securities in most emerging markets has increased significantly with time. Therefore, the market index used in the empirical analysis reflects an increasing level of diversification. Based on standard arguments from portfolio theory, this second phenomenon should induce a reduction in the volatility of the market index over time. Second, in our model we do not consider the effect of policy intervention that might have affected stock return volatility. Extensions that analyze these factors are left for future research.

5. Conclusions

In this paper we analyze the dynamic behavior of market volatility in a number of developing countries. For almost all the countries included in our sample, we find strong evidence of time-varying volatility. In particular, similar to the evidence for most developed financial markets, volatility clustering appears to characterize emerging markets. As a consequence, GARCH processes can be successfully used to model second order conditional moments in those markets. In most cases, we find a high level of persistence in volatility. Moreover, given the large number of *low and high returns* often observed in emerging markets, a conditional fat-tailed distribution is preferred to a normal density.

Given the high level of volatility that characterizes most emerging markets, we test the hypothesis that investors are rewarded with higher expected returns for undertaking market-wide risk. Surprisingly, we do not find evidence of a risk-premium for any of the countries included in the analysis.

Finally, we analyze whether the process of liberalization recently started in most emerging markets has affected return volatility. One of the arguments often used against market liberalization is that investment flows from developed markets are very sensitive to changing economic conditions in developing countries and, therefore, they increase market volatility. The empirical evidence does not support this hypothesis.

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Table 1a

Summary statistics for weekly returns (% values): January 1989 to May 1994. Returns are measured in local currencies.

Country	Mean	Median	Std. Dev.	Skewness	Kurtosis	Maximum	Minimum
Greece	0.67	0.08	4.92	0.96	6.07	22.8	-14.6
Jordan	0.39	0.18	2.50	-0.77	14.0	11.8	-16.4
Portugal	0.17	-0.05	2.36	0.99	9.92	14.9	-9.73
Turkey	1.64	0.56	8.48	0.39	4.38	33.9	-25.4
India	0.66	0.38	4.55	0.27	4.93	17.9	-14.6
Korea	0.10	-0.35	3.61	0.84	4.39	14.3	-6.97
Malaysia	0.42	0.56	2.94	-0.43	5.68	12.2	-13.2
Pakistan	1.05	0.71	3.60	0.33	4.03	12.6	-10.8
Philippines	0.58	0.39	4.03	-0.53	6.27	13.4	-21.4
Taiwan	0.25	0.18	5.86	0.30	5.81	26.3	-21.2
Thailand	0.60	0.35	4.29	-0.10	9.37	23.1	-23.5
Argentina	3.97	1.51	14.2	3.11	19.7	113.9	-33.2
Brazil	6.05	6.15	9.23	-0.09	4.43	35.1	-36.7
Chile	0.94	0.75	3.06	0.41	3.36	11.3	-7.13
Colombia	1.31	0.83	3.96	1.97	13.2	27.6	-12.9
Mexico	0.86	0.83	2.93	-0.29	3.37	9.27	-9.27
Venezuela	0.98	0.32	5.31	0.71	5.41	24.7	-16.4
USA	0.25	0.39	1.66	-0.24	4.31	5.40	-6.87
Germany	0.22	0.20	2.37	-0.37	3.89	5.88	-8.50
Japan	-0.08	-0.13	2.91	0.19	5.34	11.9	-10.9
United Kingdom	0.11	0.27	1.61	-0.27	5.06	5.88	-6.43

Table 1b

Summary statistics for weekly returns (% values): January 1989 to May 1994. Returns are measured in U.S. dollars.

Country	Mean	Median	Std. Dev.	Skewness	Kurtosis	Maximum	Minimum
Greece	0.50	-0.21	5.09	0.85	5.70	23.7	-15.4
Jordan	0.27	0.18	2.70	-0.93	12.2	11.7	-16.4
Portugal	0.13	-0.01	2.92	0.55	5.37	14.0	-9.08
Turkey	0.59	-0.24	8.48	0.13	4.67	33.4	-34.8
India	0.40	0.22	4.63	0.18	5.30	18.6	-14.6
Korea	0.04	-0.38	3.65	0.88	4.51	14.4	-7.03
Malaysia	0.43	0.58	2.96	-0.48	5.70	12.4	-13.3
Pakistan	0.86	0.33	3.57	0.38	4.08	12.6	-10.8
Philippines	0.49	0.39	4.18	-0.62	6.77	15.3	-22.6
Taiwan	0.28	0.15	6.01	0.32	5.86	27.4	-21.8
Thailand	0.60	0.42	4.30	-0.08	9.38	23.3	-23.4
Argentina	1.43	1.00	11.0	0.62	8.65	53.6	-51.2
Brazil	0.69	0.51	8.81	-0.21	3.93	23.3	-37.2
Chile	0.75	0.49	3.20	0.46	3.49	11.5	-6.70
Colombia	0.98	0.50	4.12	1.67	11.1	27.0	-13.2
Mexico	0.74	0.60	3.03	-0.25	3.32	9.27	-9.65
Venezuela	0.55	0.07	5.57	0.64	5.23	26.3	-16.6
Composite	0.27	0.30	2.53	-0.35	6.14	9.90	-10.6
Asia	0.21	0.16	3.02	-0.09	6.09	13.1	-11.3
Latin America	0.62	0.70	3.45	-0.54	5.18	11.3	-15.7
USA	0.25	0.39	1.66	-0.24	4.31	5.40	-6.87
Germany	0.26	0.29	2.87	-0.32	3.68	6.83	-9.46
Japan	0.01	-0.18	3.35	0.42	4.87	12.5	-11.8
United Kingdom	0.13	0.14	1.85	0.14	4.90	6.86	-6.20

Table 2

Ljung-Box portmanteau test statistics for the standardized residuals $uh^{-1/2}$ and the standardized residuals squared $(uh^{-1/2})^2$. The statistics are computed for two models. Model a assumes an AR(1) process with constant conditional variance. Model b assumes an AR(1) process with a GARCH(1,1) conditional variance. Both models assume a conditional normal distribution. The numbers in the table are p-values. The maximum order of autocorrelation is 10. The table also reports p-values for the likelihood ratio test of the hypothesis of conditional homoskedasticity.

	A: Local Currency					B: U.S. Dollars				
	$Q_{10}(uh^{-1/2})$		$Q_{10}(uh^{-1/2})^2$		L.R.	$Q_{10}(uh^{-1/2})$		$Q_{10}(uh^{-1/2})^2$		L.R.
	Mod.a	Mod.b	Mod.a	Mod.b		Mod.a	Mod.b	Mod.a	Mod.b	
Greece	0.15	0.42	0.00	0.93	0.000	0.13	0.42	0.00	0.68	0.000
Jordan	0.27	0.42	0.01	0.35	0.001	0.08	0.10	0.06	0.39	0.016
Portugal	0.09	0.23	0.22	0.77	0.001	0.84	0.83	0.68	0.75	0.677
Turkey	0.16	0.14	0.01	1.00	0.000	0.04	0.07	0.06	0.97	0.001
India	0.91	0.93	0.47	0.69	0.141	0.79	0.85	0.00	0.33	0.001
Korea	0.83	0.81	0.60	0.94	0.164	0.83	0.85	1.00	0.90	0.170
Malaysia	0.93	0.99	0.00	0.86	0.000	0.87	0.96	0.01	0.60	0.001
Pakistan	0.01	0.01	0.00	0.90	0.000	0.01	0.00	0.00	0.88	0.000
Philippines	0.82	0.90	0.02	0.68	0.032	0.91	0.31	1.00	0.81	0.002
Taiwan	0.12	0.93	0.00	0.42	0.000	0.01	0.01	0.00	0.19	0.000
Thailand	0.35	0.42	0.00	0.84	0.000	0.37	0.46	0.00	0.87	0.000
Argentina	0.23	0.90	0.00	0.68	0.000	0.03	0.50	0.00	0.68	0.000
Brazil	0.93	0.96	0.61	0.97	0.170	0.85	0.91	0.16	0.77	0.189
Chile	0.19	0.40	0.00	0.98	0.000	0.33	0.51	0.00	0.88	0.004
Colombia	0.06	0.31	0.00	0.94	0.000	0.33	0.62	0.00	0.31	0.000
Mexico	0.27	0.39	0.63	0.97	0.257	0.31	0.44	0.08	0.63	0.073
Venezuela	0.05	0.19	0.04	0.79	0.001	0.08	0.23	0.01	0.93	0.001
Composite	....	....	....	....	...	0.00	0.00	0.00	0.71	0.000
Asia	....	....	....	....	..	0.02	0.03	0.00	0.57	0.000
Latin America	....	....	....	....		0.15	0.21	0.00	0.50	0.000

Table 3

Measures of Kurtosis from different estimates of the AR(1)-GARCH(1,1) model. The m_4 statistic is the sample kurtosis obtained from the standardized residuals of the estimated model. The κ statistic is the (estimated) kurtosis of the conditional distribution used to evaluate the likelihood function.

	Local Currency				U.S. Dollars			
	Normal		G.E.D.		Normal		G.E.D.	
	m_4	κ	m_4	κ	m_4	κ	m_4	κ
Greece	3.80	3.0	3.95	3.85	3.64	3.0	3.74	3.69
Jordan	4.84	3.0	n.c.	n.c.	4.56	3.0	n.c.	n.c.
Portugal	4.76	3.0	n.c.	n.c.	3.45	3.0	3.49	3.80
Turkey	3.51	3.0	3.57	3.76	3.58	3.0	3.75	4.04
India	3.27	3.0	3.28	4.06	3.41	3.0	3.45	4.05
Korea	3.23	3.0	3.25	3.51	3.30	3.0	3.33	3.55
Malaysia	3.64	3.0	3.69	3.50	3.61	3.0	3.69	3.54
Pakistan	2.99	3.0	3.00	3.37	2.87	3.0	2.87	3.07
Philippines	3.09	3.0	3.13	3.30	3.13	3.0	3.16	3.40
Taiwan	3.28	3.0	3.30	3.38	3.40	3.0	3.42	3.54
Thailand	4.12	3.0	4.17	3.41	4.16	3.0	4.22	3.40
Argentina	4.04	3.0	4.22	4.05	3.86	3.0	3.92	3.61
Brazil	3.01	3.0	3.63	3.48	3.11	3.0	3.31	3.12
Chile	3.33	3.0	3.37	3.32	3.29	3.0	3.30	3.30
Colombia	3.82	3.0	3.87	4.55	4.03	3.0	4.28	4.83
Mexico	3.39	3.0	3.46	3.82	3.22	3.0	3.25	3.54
Venezuela	3.56	3.0	3.58	3.31	3.60	3.0	3.62	3.52
Composite	....	....	....	....	3.37	3.0	3.43	3.38
Asia	....	....	....	....	2.91	3.0	2.91	2.90
Latin America	....	....	....	....	3.15	3.0	3.17	3.19

n.c. indicates that the estimation procedure did not converge.

Table 4a

Estimates of AR(1)-GARCH(1,1) model. Weekly returns in local currency. A Generalized Error Distribution is assumed for asset returns.

Model:	$R_t = a + bR_{t-1} + u_t$		$u_t \vert I_{t-1} \sim GED(0, h_t, \nu)$				$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$
	a	b	ω	α	β	ν	Log.Likelihood
Greece	0.030	0.160*	2.584	0.279	0.592**	1.425***	-770.30
Jordan†	0.416***	0.091	0.306	0.071	0.848***	....	-580.52
Portugal†	-0.034	0.207*	0.984***	0.191*	0.568***	....	-578.14
Turkey	0.770*	0.150	9.926	0.219**	0.642***	1.499***	-958.39
India	0.471***	0.060	0.774	0.068*	0.886***	1.386***	-771.27
Korea	-0.197*	-0.009	5.986***	0.100	0.363*	1.623*	-728.84
Malaysia	0.470***	0.041	0.135	0.060***	0.924***	1.629*	-653.81
Pakistan	0.365	0.284***	1.546**	0.244***	0.604***	1.705	-405.84
Philippines	0.596***	0.097	0.668	0.055	0.895***	1.750	-748.76
Taiwan	0.109	0.031	2.358**	0.193***	0.721***	1.701*	-831.28
Thailand	0.655***	0.103	0.797	0.087***	0.853***	1.679*	-744.06
Argentina	0.823**	0.148**	2.397	0.266**	0.735***	1.390***	-980.79
Brazil	4.828***	0.211***	26.81**	0.093	0.540***	1.946	-991.64
Chile	0.544***	0.277***	0.756	0.115**	0.794***	1.736	-683.59
Colombia	0.548***	0.242**	0.322	0.269***	0.736***	1.245***	-652.50
Mexico	0.747***	0.203***	0.934*	0.061*	0.826***	1.476***	-681.22
Venezuela	0.273	0.224***	3.608	0.177**	0.657***	1.744	-812.82

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

† Estimates based on normal distribution.

Table 4b

Estimates of AR(1)-GARCH(1,1) model. Weekly returns in U.S. dollars. A Generalized Error Distribution is assumed for asset returns.

Model:	$R_t = a + bR_{t-1} + u_t$		$u_t \mid I_{t-1} \sim GED(0, h_t, \nu)$		$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$		
	a	b	ω	α	β	ν	Log.Likelihood
Greece	0.066	0.159*	1.641	0.145	0.773***	1.534**	-795.13
Jordan[†]	0.376***	0.071	0.674***	0.078	0.823***	....	-600.18
Portugal	0.011	-0.002	2.442	0.064	0.581	1.482**	-661.10
Turkey	-0.022	0.097	17.33*	0.224**	0.525***	1.394***	-963.25
India	0.280	0.036	1.024	0.096***	0.843***	1.390***	-770.77
Korea	-0.253	-0.007	6.101***	0.098	0.364*	1.600*	-730.99
Malaysia	0.489***	0.070	0.148	0.057***	0.925***	1.606***	-658.09
Pakistan	0.169	0.261***	1.421**	0.260***	0.597***	1.930	-403.26
Philippines	0.545**	0.069	0.886	0.080*	0.861***	1.688*	-758.61
Taiwan	0.081	0.021	2.348**	0.184***	0.739***	1.608*	-841.97
Thailand	0.665***	0.080	0.723	0.083***	0.864***	1.685	-744.88
Argentina	0.736**	0.037	1.874	0.184**	0.796***	1.573**	-953.86
Brazil	0.776	0.111	23.88**	0.070	0.594***	1.887	-989.52
Chile	0.444**	0.189***	0.565	0.086***	0.852***	1.750	-698.31
Colombia	0.425*	0.084	0.499	0.140**	0.828***	1.181***	-705.69
Mexico	0.665***	0.195	0.909**	0.073*	0.825***	1.607*	-691.08
Venezuela	-0.098	0.212***	2.940	0.146*	0.737***	1.620*	-829.96
Composite	0.245**	0.152*	0.161	0.102**	0.856***	1.697*	-583.43
Asia	0.271**	0.116*	0.141	0.080**	0.894***	2.109	-637.18
Latin America	0.672***	0.139**	0.316	0.112*	0.862***	1.832	-697.62

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

[†] Estimates based on normal distribution.

Table 5a

Estimates of AR(1)-GARCH(1,1)-M model. The conditional variance is used in the mean equation. Weekly returns in local currency. A Generalized Error Distribution is assumed for asset

Model:	$R_t = a + bR_{t-1} + ch_t + u_t$			$u_t \vert I_{t-1} \sim GED(0, h_t, \nu)$		$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$		
	a	b	c	ω	α	β	ν	Log.Likelihood
Greece	-0.266	0.147*	0.020	2.880	0.308*	0.552**	1.406***	-770.08
Jordan[†]	1.540**	0.112**	-0.318	0.443**	0.082**	0.801***	....	-577.35
Portugal[†]	-0.666	0.161	0.175	1.092**	0.186**	0.539***	....	-576.22
Turkey[†]	2.832	0.170**	-0.031	9.154	0.175	0.686***	....	-960.30
India	0.921	0.058	-0.030	0.666	0.059	0.901***	1.372***	-771.12
Korea	-0.578	-0.013	0.035	5.718	0.096	0.391	1.621*	-728.81
Malaysia	0.777	0.038	-0.050	0.125	0.058***	0.927***	1.630*	-653.54
Pakistan	-0.671	0.252***	0.125	1.573**	0.219***	0.618***	1.562*	-404.17
Philippines	0.627	0.097	-0.003	0.653	0.054	0.896***	1.749	-748.76
Taiwan	-0.474	0.024	0.027	2.341*	0.195***	0.720***	1.748	-830.51
Thailand	0.972	0.103	-0.027	0.731	0.086***	0.860***	1.680*	-743.89
Argentina	0.377	0.116**	0.010***	2.093	0.244**	0.754***	1.393***	-979.54
Brazil	22.52**	0.189***	-0.241*	1.674	0.016*	0.962***	1.799	-989.11
Chile	0.710	0.285***	-0.022	0.837	0.120**	0.779***	1.759	-683.54
Colombia	0.521**	0.239**	0.006	0.326	0.270***	0.734***	1.248***	-652.48
Mexico	0.774***	0.203***	-0.003	0.922	0.060	0.829***	1.476***	-681.22
Venezuela	-0.894	0.211***	0.061	3.002	0.150**	0.709***	1.660	-811.68

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

[†] Estimates based on normal distribution.

Table 5b

Estimates of AR(1)-GARCH(1,1)-M model. The conditional variance is used in the mean equation. Weekly returns in U.S. dollars. A Generalized Error Distribution is assumed for asset returns.

Model:	$R_t = a + bR_{t-1} + ch_t + u_t$			$u_t \mid I_{t-1} \sim GED(0, h_t, \nu)$		$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$		
	a	b	c	ω	α	β	ν	Log.Likelihood
Greece	0.371	0.159**	-0.018	1.604	0.141	0.778***	1.547*	-794.99
Jordan	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.
Portugal†	-2.293	-0.027	0.342	2.673**	0.056	0.552***	....	-662.79
Turkey	-0.952	0.077	0.014	19.106*	0.245*	0.482**	1.361***	-963.09
India	0.799	0.040	-0.035	0.910	0.086	0.859***	1.393***	-770.43
Korea	-0.089	-0.005	-0.015	6.203**	0.099	0.354*	1.601*	-730.98
Malaysia	0.656*	0.070	-0.027	0.142	0.056***	0.927***	1.613*	-658.02
Pakistan	-0.831	0.229***	0.128	1.266*	0.228***	0.638***	1.724	-401.20
Philippines	0.785	0.069	-0.018	0.884	0.081*	0.860***	1.696*	-758.56
Taiwan	-0.384	0.017	0.020	2.301*	0.183***	0.740***	1.634*	-841.47
Thailand	1.071*	0.079	-0.034	0.625	0.081***	0.874***	1.674	-744.60
Argentina	0.496	0.037	0.006	1.883	0.183**	0.796***	1.567**	-953.67
Brazil	0.521	0.110	0.004	23.969**	0.070	0.593***	1.890	-989.51
Chile	0.326	0.186***	0.014	0.527	0.084**	0.859***	1.741	-698.30
Colombia	0.335	0.084	0.010	0.493	0.140**	0.829***	1.182***	-705.66
Mexico	0.444	0.193***	0.027	0.942**	0.076*	0.819***	1.601*	-691.04
Venezuela	-1.399	0.189**	0.059	2.616	0.126*	0.767***	1.573**	-828.73
Composite	0.052	0.153*	0.053	0.180	0.111**	0.843***	1.686*	-583.02
Asia	0.187	0.117*	0.016	0.147	0.081**	0.892***	2.107	-637.14
Latin America	0.961**	0.134**	-0.034	0.314	0.109*	0.865***	1.838	-697.35

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level; n.c. = estimation procedure dis not converge.

† Estimates based on normal distribution.

Table 6a

Estimates of AR(1)-GARCH(1,1)-M model. The conditional standard deviation is used in the mean equation. Weekly returns in local currency. A Generalized Error Distribution is assumed for asset returns.

Model:	$R_t = a + bR_{t-1} + ch_t^{1/2} + u_t$			$u_t \vert I_{t-1} \sim GED(0, h_t, \nu)$		$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$		
	a	b	c	ω	α	β	ν	Log.Likelihood
Greece	-0.733	0.149*	0.204	2.760	0.305*	0.563**	1.400***	-769.99
Jordan†	2.879	0.113**	-1.316	0.465*	0.081**	0.797***	....	-577.61
Portugal†	-1.435	0.163	0.750	1.106**	0.188*	0.534***	....	-576.22
Turkey†	4.616	0.168*	-0.471	9.333	0.173	0.685***	....	-960.44
India	1.301	0.058	-0.217	0.689	0.059	0.899***	1.372***	-771.15
Korea	-1.265	-0.014	0.324	5.597	0.094	0.403	1.619*	-728.80
Malaysia	0.959	0.039	-0.200	0.127	0.058***	0.927***	1.633*	-653.66
Pakistan	-1.457	0.258***	0.645	1.619*	0.218***	0.614***	1.602*	-404.70
Philippines	1.163	0.098	-0.160	0.538	0.051	0.909***	1.738	-748.73
Taiwan	-1.490	0.024	0.359	2.322**	0.196***	0.719***	1.748	-830.18
Thailand	1.681	0.102	-0.302	0.711	0.088***	0.860***	1.684*	-743.70
Argentina	-0.530	0.121*	0.220	2.285	0.251*	0.746***	1.386***	-979.48
Brazil	40.64*	0.189***	-4.187	1.716	0.016	0.962***	1.800	-989.12
Chile	0.723	0.281***	-0.065	0.797	0.117**	0.787***	1.747	-683.58
Colombia	0.505	0.239	0.021	0.324	0.270**	0.734***	1.248***	-652.50
Mexico	0.667	0.202***	0.025	0.950	0.062	0.824***	1.475***	-681.22
Venezuela	-2.038	0.211***	0.535	3.130*	0.152**	0.701***	1.668	-811.80

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

† Estimates based on normal distribution.

Table 6b

Estimates of AR(1)-GARCH(1,1)-M model. The conditional standard deviation is used in the mean equation. Weekly returns in U.S. dollars. A Generalized Error Distribution is assumed for asset returns.

Model:	$R_t = a + bR_{t-1} + ch_t^{1/2} + u_t$			$u_t \vert I_{t-1} \sim GED(0, h_t, \nu)$		$h_t = \omega + \alpha u_{t-1}^2 + \beta h_{t-1}$		
	a	b	c	ω	α	β	ν	Log.Likelihood
Greece	0.622	0.158**	-0.137	1.593	0.140	0.780***	1.544*	-795.02
Jordan	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.	n.c.
Portugal†	-4.695	-0.028	1.815	2.765**	0.060	0.535***	....	-662.73
Turkey	-2.323	0.076	0.287	19.009*	0.250**	0.480**	1.352***	-962.99
India	1.225	0.040	-0.249	0.902	0.085	0.861***	1.390***	-770.52
Korea	-0.067	-0.006	-0.056	6.163***	0.098	0.358*	1.600*	-730.99
Malaysia	0.781	0.070	-0.119	0.143	0.056***	0.926***	1.613*	-658.04
Pakistan	-1.635	0.235***	0.660	1.322*	0.226***	0.634***	1.780	-401.82
Philippines	1.405	0.069	-0.235	0.843	0.082*	0.862***	1.703	-758.47
Taiwan	-1.368	0.014	0.311	2.266*	0.185***	0.739***	1.637*	-841.09
Thailand	1.819	0.080	-0.341	0.608	0.083***	0.874***	1.673	-744.39
Argentina	0.317	0.036	0.069	1.884	0.183**	0.796***	1.567**	-953.77
Brazil	0.513	0.111	0.032	23.969**	0.070	0.593***	1.889	-989.51
Chile	0.091	0.185**	0.122	0.519	0.083*	0.861***	1.740	-698.27
Colombia	0.240	0.083	0.064	0.489	0.139**	0.830***	1.184***	-705.66
Mexico	0.071	0.193**	0.208	0.949**	0.077*	0.817***	1.598*	-691.01
Venezuela	-2.663	0.191***	0.556	2.761*	0.128*	0.759***	1.574**	-828.88
Composite	-0.220	0.150*	0.252	0.191	0.116**	0.835***	1.687*	-582.94
Asia	0.090	0.116*	0.081	0.150	0.082**	0.890***	2.107	-637.14
Latin	1.075	0.136**	-0.142	0.314	0.108*	0.866***	1.834	-697.49

*** Significant at 1% level, ** Significant at 5% level, * Signi icant at 10% level; n.c. = estimation procedure dis not converge.

† Estimates based on normal distribution.

Table 7

Estimated unconditional volatility before and after the liberalization date. The table also includes p-values for the Likelihood Ratio test of the hypothesis that the unconditional variance changes over the two periods.

	Local Currency			U.S. Dollars		
	$\frac{\omega}{1-\alpha-\beta}$	$\frac{\omega+\delta}{1-\alpha-\beta}$	L.R. test (p-value)	$\frac{\omega}{1-\alpha-\beta}$	$\frac{\omega+\delta}{1-\alpha-\beta}$	L.R. test (p-value)
Turkey	74.170	71.615	0.999	56.876	70.972	0.708
India	13.792	21.875	0.290	14.789	21.366	0.462
Korea	10.033	12.694	0.294	10.379	12.636	0.383
Philippines	11.709	13.137	0.610	15.034	14.881	0.999
Taiwan	37.086	19.695	0.157	42.192	20.584	0.103
Argentina	191.83	34.660	0.002	119.09	27.207	0.002
Brazil	48.831	48.331	0.999	82.590	62.269	0.708
Colombia	3.524	14.258	0.012	5.087	15.530	0.009
Mexico	7.585	8.366	0.890	17.404	8.293	0.209
Venezuela	10.993	24.127	0.077	17.829	26.573	0.403

Table A1

Opening dates and regulation of emerging financial markets. The table also includes the number of securities included in the IFC index, for each country, at the beginning and the end of the sampling period.

Country	Opening Date	Degree of Openness	Number of Stocks in the Index	
			January 1989	October 1993
Turkey	August 1989	Fully open	14	36
India	November 1992	24% of the issued share capital	40	108
Korea	January 1992	10% of Capital of listed companies; 25% after July 1992	61	134
Phillipines	October 1989	Investable up to 40%	18	37
Taiwan	January 1991	Investable up to 10%	62	78
Argentina	October 1991	Fully open	24	31
Brazil	May 1991	100% of nonvoting preferred stock; 49% of voting common stock	56	70
Colombia	February 1991	Fully open	21	20
Mexico	May 1989	30% for banks; 100% for other stocks	52	71
Venezuela	January 1990	100% investable except bank stocks	13	17

Source: International Finance Corporation

Table A2a

Estimates of AR(1)-GARCH(1,1) model. Panel (A) contains test statistics to evaluate the usefulness of a GARCH parameterization. Panel (B) contains estimates of the model when no risk component is included in the mean equation. Panel (C) contains estimates of the model when the conditional variance is used as a measure of risk. Panel (D) contains estimates of the model when the conditional standard deviation is used as a measure of risk. Weekly returns are in local currencies. A conditional Generalized Error Distribution is assumed for asset returns.

A: General Test Statistics

	Constant Variance		GARCH		Normal		GED		
	$Q_{10}(uh^{-1/2})$	$Q_{10}(uh^{-1/2})^2$	$Q_{10}(uh^{-1/2})$	$Q_{10}(uh^{-1/2})^2$	m_4	κ	m_4	κ	L.R.(α=β=0)
U.S.	0.36	0.07	0.60	0.51	3.37	3.00	3.41	3.32	0.000
Germany	0.95	0.01	0.99	0.59	3.21	3.00	3.22	3.16	0.004
Japan	0.67	0.00	0.64	0.27	3.89	3.00	3.92	3.83	0.001
U.K.	0.74	0.00	0.85	0.63	3.32	3.00	3.37	3.63	0.000

B: AR(1)-GARCH(1,1) Model

	a	b	c					Log.Likl.
U.S.	0.275^{***}	-0.110	....	0.014	0.036^{*}	0.956^{***}	1.738	-506.996
Germany	0.316^{**}	0.003	....	0.242	0.070^{***}	0.881^{***}	1.857	-611.102
Japan	-0.075	0.011	....	0.694^{**}	0.102^{**}	0.797^{***}	1.470^{***}	-652.509
U.K.	0.234^{**}	0.016	....	0.443	0.183	0.609^{*}	1.560^{*}	-488.685

C: AR(1)-GARCH(1,1) Model: Variance in Mean Equation

	a	b	c					Log.Likl.
U.S.	-0.121	-0.115^{*}	0.202	0.008	0.030	0.963^{***}	1.695	-505.418
Germany	0.328	0.003	-0.003	0.242	0.070^{***}	0.880^{***}	1.858	-611.102
Japan	-0.301	0.012	0.037	0.700^{**}	0.100^{**}	0.796^{***}	1.489^{***}	-652.392
U.K.	0.082	0.015	0.082	0.464	0.195	0.586	1.591^{*}	-488.406

D: AR(1)-GARCH(1,1) Model: Standard Deviation in Mean Equation

	a	b	c					Log.Likl.
U.S.	-0.511	-0.116^{*}	0.572	0.006	0.030^{*}	0.964^{***}	1.693	-505.341
Germany	0.293	0.003	0.011	0.242	0.070^{***}	0.881^{***}	1.857	-611.102
Japan	-0.608	0.013	0.217	0.706^{**}	0.101^{**}	0.795^{***}	1.491^{***}	-652.376
U.K.	-0.164	0.017	0.296	0.438	0.188	0.604^{*}	1.593^{*}	-488.311

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

Table A2b

Estimates of AR(1)-GARCH(1,1) model. Panel (A) contains test statistics to evaluate the usefulness of a GARCH parameterization. Panel (B) contains estimates of the model when no risk component is included in the mean equation. Panel (C) contains estimates of the model when the conditional variance is used as a measure of risk. Panel (D) contains estimates of the model when the conditional standard deviation is used as a measure of risk. Weekly returns are in U.S. dollars. A conditional Generalized Error Distribution is assumed for asset returns.

A: General Test Statistics

	Constant Variance		GARCH		Normal		GED		
	$Q_{10}(uh^{-1/2})$	$Q_{10}(uh^{-1/2})^2$	$Q_{10}(uh^{-1/2})$	$Q_{10}(uh^{-1/2})^2$	m_4	κ	m_4	κ	L.R.($\alpha=\beta=0$)
U.S.	0.36	0.07	0.60	0.51	3.37	3.00	3.41	3.32	0.000
Germany	0.82	0.01	0.82	0.92	3.11	3.00	3.11	3.19	0.002
Japan	0.46	0.04	0.50	0.10	3.72	3.00	3.74	4.24	0.272
U.K.	0.58	0.28	0.72	0.55	3.56	3.00	3.64	3.78	0.029

B: AR(1)-GARCH(1,1) Model

	a	b	c					Log.Likl.
U.S.	0.275***	-0.110	....	0.014	0.036*	0.956***	1.738	-506.996
Germany	0.345**	-0.068	....	0.448	0.103**	0.839***	1.835	-666.162
Japan	-0.156	0.028	....	5.066	0.077	0.410	1.327***	-707.972
U.K.	0.160	0.017	....	1.012	0.145	0.469	1.491***	-522.745

C: AR(1)-GARCH(1,1) Model: Variance in Mean Equation

	a	b	c					Log.Likl.
U.S.	-0.121	-0.115*	0.202	0.008	0.030	0.963***	1.695	-505.418
Germany	0.201	-0.070	0.022	0.468	0.106**	0.833***	1.846	-666.107
Japan	-0.747	0.027	0.061	4.025	0.070	0.522	1.330***	-707.935
U.K.	0.132	0.018	0.011	1.022	0.146	0.465	1.492***	-522.741

D: AR(1)-GARCH(1,1) Model: Standard Deviation in Mean Equation

	a	b	c					Log.Likl
U.S.	-0.511	-0.116*	0.572	0.006	0.030*	0.964***	1.693	-505.341
Germany	0.020	-0.070	0.130**	0.467	0.106**	0.834***	1.848	-666.097
Japan	-1.505	0.026	0.433	3.791	0.068	0.547	1.330***	-707.937
U.K.	0.154	0.017	0.004	1.013	0.145	0.469	1.492***	-522.745

*** Significant at 1% level, ** Significant at 5% level, * Significant at 10% level.

Figure 1a. Conditional Variance and Opening Date

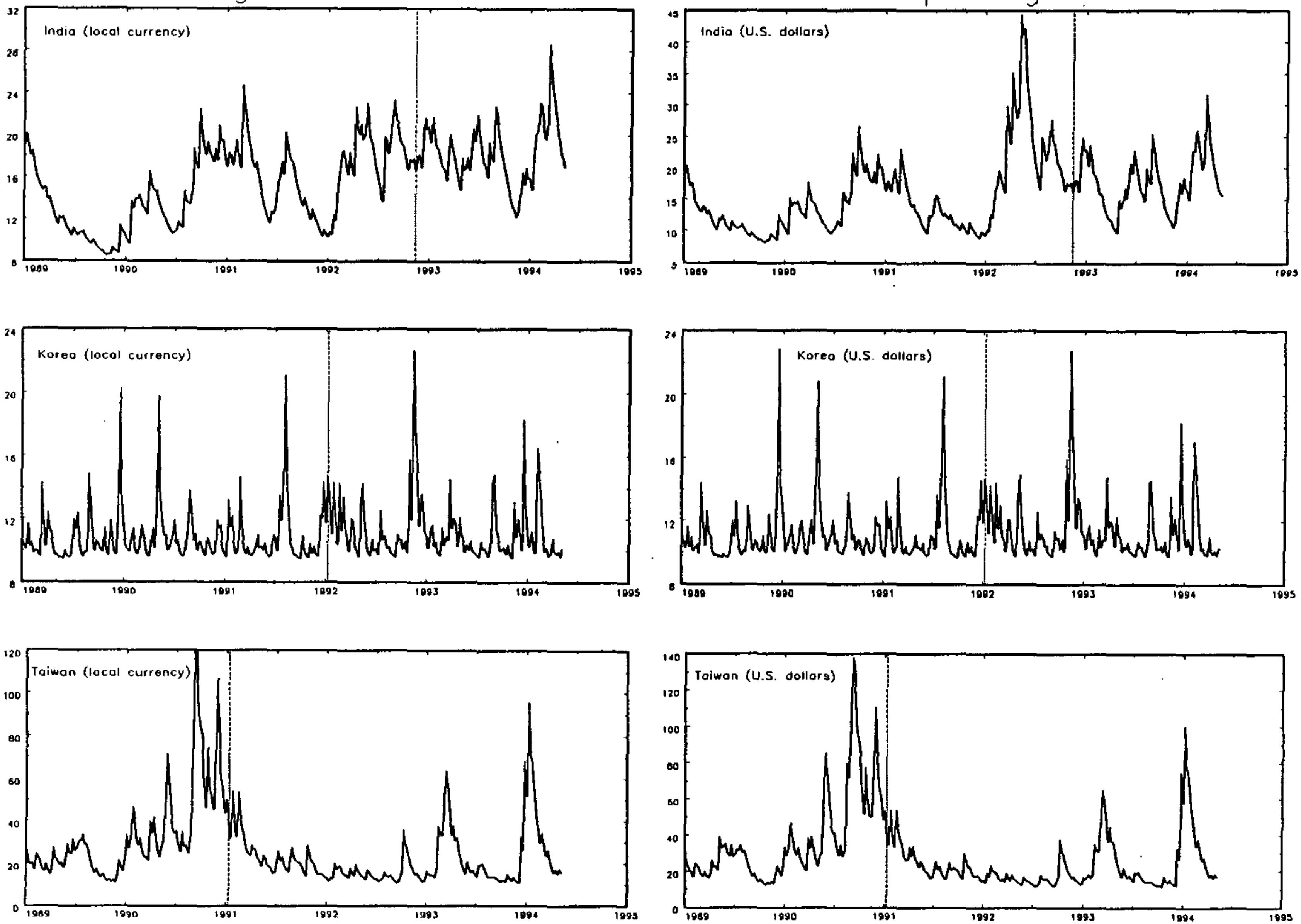

Figure 1b. Conditional Variance and Opening Date