Explaining Stock Price Volatility in Emerging Markets with Macro and Balance of Payment Variables

by

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Abstract

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Abstract: The log of stock price volatility is modelled as a dependent variable for 23 emerging markets. The conditional variance computed by the GARCH model estimates stock price volatility. The explanatory variables are the log of interest rate, log of the U.S. short-term Treasury bill rate, log of exchange rate, percentage change in current account, percentage change in deficit/ surplus, change in consumer prices and the square of the inflation rate. In the first section of the study, this model is tested on the 23 emerging markets. Coefficients that demonstrate statistical significance are those of the log of the interest rate, the log of U.S. Treasury bill rate, the log of exchange rate, the change in consumer prices and the square of the inflation rate. In the second section of the study, a Vector Autoregressive (VAR) system of equations is constructed for all the countries with the United States added to

it. A Vector Autoregressve system is run for the logs of stock price volatility for all the countries where the volatility can be computed. Statistically significant relationships are observed for the region of Latin America, the Latin American countries amongst themselves and with countries in the other regions of Europe and Asia. Not many of the countries show a statistically significant relationship with the United States.

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Chapter 1

Introduction

This dissertation explains changes in stock price volatility over time in emerging markets. Emerging markets are defined according to the World Bank's definition, IFC Investables. Stock price data for twenty-three emerging markets are taken from the regions of Latin America, Europe and Asia. This study explains this volatility with macro and balance of payment variables from 1989 to 1994.

Previous work has been done regarding stock return volatility in emerging markets. De Santis and Imrohoroglu (1994), for example, find evidence that stock return volatility is time-varying. Moreover, they find time-varying volatility is predictable. They also do not find any systematic effect of market liberalization on stock return volatility. Kim and Singal (1993) find that contributing factors to stock return volatility are volatility of industrial production and recessions in the business cycle, as measured by a dummy variable.

Stock price volatility is defined here as the forecast error to a prediction of stock price. It is estimated as the standard deviation of the conditional variance (the forecast variance) using the Exponential General Autoregressive Conditional Heteroscedastic (1,1) (EGARCH (1,1)) specification. The conditional variance is computed as a function of lagged values of past variances towards a better prediction of that stock price volatility.

The stock price volatility is measured by the standard deviation of the conditional variance to be explained in terms of the log of explanatory variables. The log of the standard deviation is taken and the explanatory variables are measured by logarithms and percentage changes.

This thesis has two hypotheses. The first is that the log of standard deviation for each emerging market is a function of the log of nominal short-term interest rate, the log of the U.S. short-term Treasury bill rate, the log of the nominal exchange rate, percentage change in current account, percentage change in deficit/surplus, log of exports, the percentage change in consumer prices and the inflation rate squared (a measure of hyperinflation). The second hypothesis is that the logs of stock price volatility in these emerging markets are interdependent and that the U.S. directly affects all of these emerging markets. In this second hypothesis, the United States is included in the estimation. A system of equations is drawn up linking countries that have stock prices from the same time period. A Vector Autoregression (VAR) model is run to estimate this system of equations. The effect of one emerging market on the other is measured and discussed.

The contribution of this study is the following. First, this study includes more countries, such as the new economies of Eastern Europe, than in any other study seen to date. Second, this study uses more recent data, through 1994, than used in previous studies. Third, this study explains the log of standard deviation with domestic macro and balance of payment variables that has not been done before. Fourth, this study looks at how the change in volatility of the United States affects the respective changes in volatility of these emerging markets that has not been done to date.

The study consists of six chapters. The first is the introduction. The second is a literature review of existing models used on financial time series data and on emerging markets in particular. The most pertinent papers will be described in detail. The General Autoregressive Conditional Heteroscedasticity (GARCH) model will be described that is used to model stock price volatility and the third chapter is on how the stock price volatility is computed. It puts the stock price volatility in its context in the econometrics literature. Like the literature review, it explains the econometric model of the GARCH model and goes further to explain the nature of the Exponential GARCH that is used to estimate the stock price volatility. The fourth is a description of the study's model with specific reference to its assumptions, its hypotheses, a justification of its chosen explanatory variables and its econometric specification. The fifth is the model empirically testing the first and second hypotheses across twenty-three emerging markets and including the United States for the second hypothesis. The sixth chapter is a conclusion.

The findings of the study are the following. In the individual country estimation, the log of the short-term nominal interest rate, the log of the U.S. Treasury bill rate and the log of the exchange rate show explanatory power. The inflation and inflation squared term also have explanatory power. In the VAR estimation with the United States included, there is evidence that the logs of stock price volatility are correlated, particularly by regions of Asia, Latin America and Europe. The highest correlations seem to be between the Latin American countries and countries of Europe and Asia; not as many are correlated with the major market of the United States. The data demonstrate that there is an interdependence between these markets as in the second hypothesis, but indicate that these markets are not directly affected by the

United States as might have been supposed.

Chapter 2

Literature Review-Emerging Markets

Most Pertinent Papers

There are a few papers that have been used as the basis of this study. They will be discussed in detail to see how stock price volatility is measured and which variables might be able to explain it.

Engle (1982)

Engle (1982) is credited with being the first to model the variance as conditioned on past values. This paper proposes a class of models where the variance does depend upon the past and argues for its usefulness in economics. Consider initially the random variable y_t drawn from the conditional density function $f(y_t \mid y_{t-1})$ with error term ε_t. The forecast of today's value is based upon the past information under standard assumptions that $E(\varepsilon_t)=0$ (white noise) and $E(\varepsilon_t\ \varepsilon_{t+s})\neq 0$. The forecast is $E(y_t \mid y_{t-1})$ which depends upon the value of the conditioning variable y_{t-1}. The variance of a one-period forecast is given by $V(y_t \mid y_{t-1})$. It recognizes that the conditional forecast variance depends upon past information.

Consider initially a first-order autoregressive process of $y_t=\gamma y_{t-1}+\varepsilon_t$. The error term ε_t is white noise and $V(\varepsilon_t) = \sigma_t^2$. The conditional mean of y_t is γy_{t-1} and in this particular case, the unconditional mean is zero. The standard approach of heteroscedasticity is to introduce an exogenous variable x_t which predicts the variance. The model could be of the form $y_t=\varepsilon_t x_{t-1}$ with $Var(\varepsilon_t) = \sigma^2_t$. The variance of y_t is simply $\sigma_t^2 x^2_{t-1}$.

The standard solution to the problem is considered unsatisfactory. It requires a specification of the causes of the changing variance individually rather than recognizing that both conditional means and variances may jointly evolve over time. This necessary specification presents a problem in heteroscedasticity corrections. It is perhaps for this reason that they are rarely considered in time series data. The author says that this approach is not successful.

In another approach the conditional variance is allowed to depend on past realizations of the time series. The simple case is $y_t=\varepsilon_{t-1}y_{t-1}$ and the conditional variance is $\sigma_t^2 y_{t-1}^2$ just as it was $\sigma_t^2 x_{t-1}^2$ when the model was $y_t=\varepsilon_t x_{t-1}$. The unconditional variance, however, is either zero or infinity, which is not a desirable property. It would be preferable for the variance to be finite.

A third model is $y_t=\varepsilon_t h_t^{1/2}$ in which $h_t=\alpha_0 + \alpha_1\, y_{t-1}^2$ with $V(\varepsilon_t) = 1$. This is an Autoregressive Conditional Heteroscedasticity (ARCH) model. ψ_t denotes the information set available at time t under the assumption that h is normally distributed. Conditional densities can be written in terms of the information set ψ_t.

1) $\psi_t \mid \psi_{t-1} \sim N(0,h_t)$

2) $h_t = \alpha_0 + \alpha_1 y_{t-1}^2$

3) $h_t = h(\, y_{t-1}, y_{t-2}, \ldots y_{t-p}, \alpha)$ where in the variance function p, is the order of the ARCH process and α is a vector of unknown parameters.

The general ARCH regression is obtained by assuming that the mean of y_t is given as $x_t\beta$. $x_t\beta$ is a linear combination of lagged endogenous and exogenous variables included in the information set ψ_{t-1}. β is the vector of unknown parameters. The above equations can be rewritten as

4) $y_t \mid \psi_{t-1} \sim N(x_t\beta, h_t)$

$h_t = h(\, \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots \varepsilon_{t-p}, \alpha)$

$\varepsilon_t = y_t - x_t\, \beta$

It has a variety of characteristics which makes it attractive for applications. In econometrics forecasters have found that their ability to predict future stock price varies from one period to another. It suggests the usefulness of the ARCH since the forecast variance may change over time. Moreover, the forecast variance is predicted by past forecast errors. McNees says that "the inherent uncertainty or randomness associated with different forecast periods seems to vary widely over time. The small and large errors tend to cluster together in contiguous time periods"[1].

This model is considered to have applications to the theory of finance in the following fashion. The portfolio of financial assets is held as functions of expected means and variances of the rates of return. Any shifts in asset demand must be associated with changes in expected means and variances of the rates of return. If the mean is assumed to follow a standard regression or time series, the variance is immediately constrained to be constant over time.

Empirical work using time-series data frequently adopts ad hoc methods to measure and allow shifts in the variance over time. One example of this is Khan (1977), who resorts to the notion of "variability" rather than variance, using the absolute value of the first difference of the inflation rate. Similarly it is intuitive that the variance of a stock price is related to the

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[1] McNees, S.S. "The Forecasting Record for the 1970's," New England Economic Review, September/October 1979,52.

previous period's variance of stock price. The variance of stock price is then conditioned by its past values. A shift in asset demand would reflect the effect of these past values.

The likelihood function for an ARCH model is constructed in the following way. Suppose y_t is generated by an ARCH process described in

1) $y_t \mid \psi_{t-1} \sim N(0,h_t)$

2) $$h_t = \alpha_0 + \alpha_1 y_{t-1}^2$$

3) $h_t = h(y_{t-1}, y_{t-2}, \ldots y_{t-p}, \alpha)$ where p is the order of the ARCH process and α is a vector of unknown parameters. The properties of this process can easily be determined by repeated application of the relation Ex=(Ex|y). The mean of y_t is zero and all covariances are zero. The unconditional variance is given by $\sigma_t^2 = Ey_t^2 = Eh_t$.

For many functions h and values of α, the variance is independent of t. y_t is covariance stationary if and only if the associated characteristic equation has all roots outside the unit circle or has a finite variance. The joint density is the product of all conditional densities. The log likelihood, therefore, is the sum of the conditional normal log likelihoods corresponding to the following equations

1) $y_t \mid \psi_{t-1} \sim N(0,h_t)$

3) $h_t = h(y_{t-1}, y_{t-2}, \ldots y_{t-p}, \alpha)$

The log likelihood function is, apart from some constants in the likelihood function, the following:

$$l = \frac{1}{T}\sum_t^T = l_t$$

$$l_t = -\frac{1}{2}\log h_t - \frac{1y^2}{2h_t}$$

To estimate the unknown parameters α, the likelihood function can be maximized.

The first-order conditions are

$$7) \frac{\delta l_t}{\delta \alpha} = \frac{1}{2h_t} * \frac{\delta h}{\delta \alpha}\left(\frac{y_t^2}{h_t} - 1\right)$$

and the Hessian is

$$8) \frac{\delta^2 l_t}{\delta \alpha \delta \alpha'} = -\frac{1}{2h^2{}_t}\frac{\delta h}{\delta \alpha}\frac{\delta h}{\delta \alpha'}\left(\frac{y_t^2}{h_t} - 1\right) + \left[\frac{y_t^2}{h_t} - 1\right] * extra\ terms$$

The conditional expectations of the second term is zero given ψ_{t-m-1}. Hence the information matrix is the negative expectation of the Hessian averaged over all observations

$$I_{aa} = \sum_t \frac{1}{2T} E\left[\frac{1}{h_t^2}\frac{\delta h_t}{\delta \alpha'}\frac{\delta h_t}{\delta \alpha'}\right]$$

If the h function is linear in the p's, it can be written as

11) $h_t=\alpha_0+\alpha_1 y_{t-1}^2+ \ldots..\alpha_p y_{t-p}^2$

While the y terms are in squared terms, the α terms are linear through the pth term. If the h function is linear in the p's, the information gradient and matrix have a particularly simple form.

Let $z=(1, y_{t-1}^2, .., y_{t-p}^2)$ and $\alpha'=(\alpha_0, \alpha_1, \ldots \alpha_p)$ so that

11) $h_t=\alpha_0+\alpha_1 y_{t-1}^2+ \ldots..\alpha_p y_{t-p}^2$

12) $h_t=z_t \; (1, y_{t-1}^2, \ldots, y_{t-p}^2)\,(\alpha_0, \alpha_1, \ldots, \alpha_p)$

The gradient (first-order condition) then becomes as in 13) and the information matrix becomes as in 14)

13) $$\frac{\delta l}{\delta \alpha}=\frac{1}{2h_t}z_t\left[\frac{y_t^2}{h_t}-1\right]$$

14) $$I(\theta)_{aa}=\frac{1}{2T}\sum_t\left(\frac{z_t' z_t}{h_t^2}\right)$$

This specification is relevant to estimating an ARCH model.

The distribution of the First-Order Linear ARCH process is that in the first-order linear model

1) $y_t \mid \psi_{t-1} \sim N(0,h_t)$

2) $h_t = \alpha_0 + \alpha_1 y_{t-1}^2$

A large observation for y will lead to a large variance for the next period's distribution. The memory process is confined to one period. If α_1=0, y_t will be Gaussian white noise. If α_1>1, successive observations will be dependent through higher-order moments. If α_1 is too large, the variance of the process will be infinite.

The first order ARCH process generates data with fatter tails than the normal density distribution. No procedure (to the author's knowledge) has made use of the fact that temporal clustering of outliers can be used to predict their occurrence and minimize their effects. The ARCH model does take advantage of this temporal clustering of outliers.

The conditions for a first-order linear ARCH process to have a finite variance and be covariance stationary can be generalized for the pth order process. The pth order linear ARCH processes with $\alpha_0>0$, $\alpha_1 .. \alpha_p \geq 0$ is covariance stationary if and only if the associated characteristic equation has all roots outside the unit circle.

The stationary variance is given by

$$E(y_t^2)=\frac{\alpha_0}{1-\sum_{j=1}^{P}\alpha_i}$$

A description of the ARCH regression models is the following. If the ARCH random variables discussed thus far have non-zero means ($x\beta$), then a regression framework is appropriate. The model is made up of a linear combination of lagged endogenous and exogenous variables. The model's equations are therefore the following:

1) $y_t \mid \psi_{t-1} \sim N(x_t\beta, h_t)$

$$h_t = h(\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots \varepsilon_{t-p}, x_t, x_{t-1}, \alpha)$$

$$\varepsilon_t = y_t - x_t\,\beta$$

The disturbances in the linear regression follow an ARCH process. In the pth linear order case, the specification and likelihood function are given by

$$l = \frac{1}{T}\sum_{t=1}^{T} l_t$$

$$l_t = -\frac{1}{2}\log h_t - \frac{1\varepsilon_t^2}{2h_t}$$

The likelihood function can be maximized with respect to the unknown parameters α and β.

The Ordinary Least Squares (OLS) estimator of β is still consistent as X and ε are uncorrelated through the definition of the regression as a conditional expectation. If the x's can be treated as fixed constants then the least squares standard errors will be correct. If there are lagged dependent variables in x_t, however, the least squares estimators will not be consistent.

The standard errors as conventionally computed will not be consistent. The squares of the disturbances will be correlated with the squares of the x's. OLS estimates may be unbiased and consistent but they do not achieve the Cramer-Rao lower bound. The maximum likelihood estimation is asymptotically superior as a result, since it achieves the Cramer-Rao lower bound of efficiency.

The procedure recommended to estimate an ARCH process is the following. First estimate β by OLS and obtain residuals. From these residuals, an efficient estimate of α can be constructed for the h function. Based on these α-hat estimates, the efficient estimates of β are found. The iterations are calculated using the scoring algorithm. Each step, for a parameter vector ϕ, produces the estimates ϕ^{i+1} based on ϕ^i according to

27) $\phi^{i-1}=\phi^i + [I(\theta)_{\phi\phi}]^{-1} 1/T\Sigma_t \delta l^i/\delta\phi$ where $I(\theta)$ and $\delta l^i/\delta\phi$ are evaluated at ϕ^i. The advantage of this algorithm is that it requires only first derivatives of the likelihood function. It uses the statistical properties of the problem to tailor the algorithm to this application. For the p-the order linear model, the scoring step for α can be rewritten by substituting 12), 13) and 14) and interpreting y_t^2 as the residuals e_t^2 into 27)

27) $\phi^{i-1}=\phi^i + [I(\theta)_{\phi\phi}]^{-1} 1/T\Sigma\delta l^i/\delta\phi$

The gains in efficiency from using the maximum likelihood estimation are calculated for a following special case. Consider the linear and stationary ARCH model with p=1 and all x_t exogenous. The Gauss-Markov theorem applies and the OLS has a variance of $\sigma^2(x'x)^{-1}=E\varepsilon_t^2(\Sigma_t x_t'x_t)^{-1}$. Since the disturbance process is stationary, the variance-covariance matrix is proportional to that of OLS and the relative efficiency depends only upon the scale factors. The relative efficiency of MLE to OLS is

$$R=E(h_t^{-1}+2\varepsilon_t^2\alpha_t^2/h_{t-1}^2)\sigma^2$$

After the substitution of $h=\alpha_0+\alpha_1\varepsilon_{t-1}^2$

$$\sigma^2 = \alpha_0/1-\alpha_1$$

$\gamma=\alpha_1/1-\alpha_1$ into the above R function

substituting $u=\varepsilon\sqrt{(1-\alpha_1)/\alpha_0}$ because ε_{t-1}^2 and ε_{t-2}^2 have the same density, and some further calculations, the expression for the relative efficiency becomes

$$R = E((1+\gamma)/(1+\gamma u^2)) + 2\gamma^2 E[u^2/(1+\gamma u^2)^2]$$

where u has variance 1 and mean zero. There is a gain in efficiency whenever $\gamma\neq 0$. For α_1 close to unity, the gain in efficiency from using a maximum likelihood estimator would be large. The maximum likelihood estimation yields more efficient estimates than OLS estimates for the first-order linear ARCH process.

Bollerslev (1986)

Bollerslev (1986) discusses the importance of the work of Engle (1982) for addressing the clustering of residuals in financial data. While conventional time series and econometric models operate under an assumption of constant variance, the ARCH (Autoregressive Conditional Heteroscedastic) process introduced in Engle (1982) allows this conditional variance to change over time. The variance is conditioned by a function of past errors leaving the unconditional variance constant.

This paper introduces the GARCH(p,q) process. It explains the theoretical background and justifies its use over the ARCH(q) process used for this study. It has been included for this reason.

This ARCH model that allows conditional variance to change has proven useful in modeling economic phenomena such as the inflation rate. These models are constructed recognizing that the uncertainty of inflation tends to change over time. An arbitrary linear declining lag structure is assigned to the conditional variance equation to take into account the long memory typically found in empirical work. Estimating a totally free lag distribution often will lead to violation of the non-negativity constraints. The strength of the paper is that it introduces a more general class of processes, GARCH. It allows a more flexible lag structure than the ARCH model. The strength of the GARCH process is that it incorporates a moving average process in addition to an autoregressive process. The extension of ARCH to GARCH is comparable to extending AR to ARMA. The moving average process can be viewed as a learning mechanism.

The ARCH process introduced by Engle (1982) explicitly recognizes the difference between the unconditional and conditional variance allowing the latter to change over time as a function of past errors to improve forecasting it. It has been found that empirical applications of the ARCH model have required a long lag in the conditional variance and a fixed lag structure has been imposed to avoid problems with negative variance parameter estimates. It is therefore of practical interest to extend the ARCH class of models to that of the GARCH(p,q) to allow for a longer memory structure.

Let ε_t denote a real-valued discrete-time stochastic process and ψ_t be the information set through time t. The GARCH process is given by $\varepsilon_t = y_t - x_t'\beta$ where $\varepsilon_t \,|\psi_{t-1} \sim N(0,h)$ and

$$h_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{i=1}^{p} \delta_i h_{t-i}$$

While ε_t is assumed to be normally distributed, the distribution of the data residuals from the stochastic process does not follow a normal distribution. That accounts for the leptokurtic trend in the data.

In a GARCH(p,q) process, if p=0, the ε_t process reduces to an ARCH(q) process. For p=q=0, ε_t is simply white noise. In contrast to the ARCH model where the conditional variance is a linear function of past sample variances only, the GARCH(p,q) process allows lagged conditional variances to enter the current conditional variance. The lagged conditional variances correspond to some sort of learning mechanism.

In the GARCH(p,q) regression model, the ε_t's are innovations in the linear regression $\varepsilon_t = y_t - \beta' x_t$. In the GARCH(1,1) process, the mean lag in the conditional variance equation is a function of the memory term δ. The coefficient of kurtosis shows that the GARCH(1,1) process is heavy-tailed, even though ε_t is assumed to be normally distributed. This is a property it shares with the ARCH(q) process.

For the GARCH (1,1) process, the equations are the following:

$\varepsilon_t | \psi_{t-1} \sim N(0,h_t)$

$h_t = \alpha_0 \alpha_1 \varepsilon_{t-1}{}^2 + \delta_1 h_{t-1}$

The mean lag

in the conditional

variance equation is

given by

$$\zeta = \sum_{i=1}^{\infty} i \frac{\gamma_i}{\sum_{i=1}^{\infty} \gamma_i = (1-\delta_i)^{-1}}$$

which is a function of the memory term δ. No proof for this result is given.

The estimation of the GARCH regression model uses the maximum likelihood estimation. The log likelihood function is similar to that of the ARCH process: $l_t = -1/2 \log h_t - ½\, \varepsilon_t^2 h_t^{-1}$

$$\frac{\delta l_t}{\delta\beta} = \varepsilon_t \frac{x_t}{h_t} + \frac{1}{2} h_t^{-1} \frac{\delta h_t}{\delta\beta} \left(\frac{\varepsilon_t^2}{h_t} - 1\right)$$

where

$$24)\ \frac{\delta h_t}{\delta\beta} = -2 \sum_{j=1}^{q} \alpha_j x_{t-j} \varepsilon_{t-j} + \sum_{j=1}^{p} \delta_j \frac{\delta h_{t-j}}{\delta\beta}$$

The main difference between the ARCH and the GARCH models is the inclusion of the recursive part of 24), the last term. For this reason all the calculations of gradients and information matrices have not been included as they are similar to those of the ARCH model from Engle (1982).

The reason that the maximum likelihood function is used is that the nonlinear estimation is more efficient. The process used is similar to the one used for the ARCH(q) process, but with the addition of the recursive part. The recursive terms complicate use of Newton's method of scoring for GARCH. Instead, the Berndt, Hall, Hall and Hausman (1974) algorithm turns out to be more convenient. If θ^i denotes the parameter estimates after the ith iteration, θ^{i-1} is then calculated from

$$\theta^{(i-1)}=\theta^{(i)}+\lambda_i\left(\sum_{t=1}^{T}\frac{\delta l_t}{\delta\theta}\frac{\delta l_t}{\delta\theta'}\right)^{-1}\sum_{t=1}^{T}\frac{\delta l_t}{\delta\theta}$$

θ^{i-1} is evaluated at θ^i and λ_i is a variable step length chosen to maximize the likelihood function in the given direction. The maximum likelihood estimate of θ_T is strongly consistent for θ_0 and asymptotically normal with mean θ_0 and covariance $-E(\delta^2 l_t/\delta\theta\delta\theta')^{-1}$. The formal test for the presence of GARCH is a Lagrange Multiplier test. The null hypothesis is that there is no GARCH effect.

DeSantis and Imrohoroglu (1994)

DeSantis and Imrohoroglu (1994) examine whether stock return volatility changes over time. They start from the premise that there has been a revival of interest in emerging markets after the debt crisis in the early

Eighties. The recognition of the volatility of emerging stock markets has been tracked by the estimation of variances of asset returns over relatively long periods of time. They therefore feel that measuring volatility over a long period of time is not of use to investors who have to make portfolio decisions on portfolio allocation. The purpose of their study is to characterize the dynamic behavior of stock returns and volatility for a number of emerging markets.

There are four questions that their study addresses: 1) whether stock return volatility changes over time 2) how frequent are big surprises in emerging stock markets 3) whether there is any relationship between market risk and expected returns 4) whether liberalization of emerging financial markets affects return volatility.

The ARCH model is identified as the most appropriate model for this stock return data. It has been applied to traditional models of asset pricing, problems of optimal portfolio choice, strategies of dynamic hedging and pricing of derivative securities. The ARCH model has been particularly successful in applications to high frequency financial data.

The authors depart from the assumption of normality of returns and assume that the returns follow a fat-tailed distribution. They find that this distribution increases the goodness of the fit of the model, supporting the idea that big surprises are often observed in emerging markets.

GARCH models have the feature that the implied unconditional distribution is leptokurtic. The authors characterize this phenomenon as the non-normality of conditional distributions. This property is appealing because analysis of high frequency financial data shows that the empirical distribution of asset returns has fatter tails than the normal density function. The residuals can be standardized as $z_t=u_t h_t^{-1/2}$ from the model showing that their distribution is leptokurtic. The GARCH process of Bollerslev (1986) is used to model the behavior of the conditional variance over time. The GARCH model can accommodate volatility clustering.

They model the volatility of stock returns as the conditional variance computed when estimating the GARCH(1,1) model. The point of this approach is recognizing that the errors change over time and that it is easier to calculate a forecast error for volatility in a time series than across a portfolio, as in the standard deviation, for each observation in a time series. The latter method would require calculation of a "portfolio" standard deviation for each single observation. In addition to the cumbersome nature of performing this task, time series is subject to autocorrelation. Since errors are correlated as forecasts, it makes more sense to model the volatility between time periods rather than across the countries in the study.

They model volatility as an explanatory variable to stock market returns. A Generalized Error Distribution (GED) is assumed for asset returns. This distribution can coincide with the normal distribution, but it is more general. Maximum likelihood estimation can still be used with this type of distribution.

The paper's principal regression equation is $R_t = a + bR_{t-1} + ch_t^{\,p}\big|_{p=.5,\,1}$ in which the error term is assumed to be $u|I_{t-1} \sim GED(0,h_t,v)$ and $h_t = \omega + \alpha u^2_{t-1} + \beta h_{t-1}$. R_t is the market index assumed to follow a simple AR(1) process. The coefficient c is the conditional variance used to model risk. The model is an AR(1)-GARCH(1,1) specification. The GARCH(1,1) specification implies a memory lag of one period as well as autocorrelation of one period as in the AR(1) process. Since in this specification the variance of previous periods are included, it differs from that of the Capital Asset Pricing Model (CAPM) model. That model sets the expected return as a linear function of its variance from the same period. But the specification of modeling risk as the return variance, as opposed to the present value of stock earnings, is consistent with the CAPM and as a specification, has gained support as a result.

The stock return volatility, modelled as conditional variance and as a standard deviation, shows some explanatory power in two of the seventeen countries they use. The conditional variance shows explanatory power in Argentina and Brazil when returns are measured in local currency. It does not show explanatory power in any of the seventeen countries used when the returns are measured in U.S. dollars. When the standard deviation of the conditional variance is used to measure stock return volatility, it does not show explanatory power in any of the countries tested, using data in local currency or U.S. dollars.

An issue raised of particular interest is the effect of liberalization of markets. One argument is that investment flows towards emerging markets would be volatile in response to opening up of markets. In fact, stock price volatility is a consequence of the perceived volatility of these investment flows to emerging markets. De Santis and Imrohoroglu test for the effect of liberalization on return volatility of investment for the countries Argentina, Brazil, Colombia, India, Korea, Philippines, Turkey, Taiwan and Venezuela. They summarize their results by saying that they do not find empirical evidence of a positive correlation between market liberalization and volatility.

As defined by a dummy variable, the liberalization variable would be equal to 0 before the liberalization date and 1 afterwards. Its coefficient, δ, is only statistically significant at the 10% level for Argentina, Colombia and Venezuela. It does not appear to be an effective explanatory variable.

Kim and Singal (1993)

Kim and Singal (1993) examine the effect of privatization of stock markets on the volatility of stock prices in emerging markets. The purpose of their paper is to examine the issues of recent experiences of opening up markets by emerging economies. The question is whether there are changes in stock prices, changes in the volatility flows and whether there is volatility of portfolio flows following market openings. To explain the change in stock price volatility, several potential reasons are explored. They include volatility of portfolio flows, exposure to foreign stock markets and changes in macroeconomic factors. The authors examine volatility of stock prices but use return data to calculate that volatility. They maintain that the volatility is explained by business cycles and use a dummy variable to capture the effect of recessions. They model stock price volatility with the following explanatory variables: volatility of portfolio flows, exposure to foreign stock markets, and changes in domestic macroeconomic factors such as volatility of industrial production.

Stock prices are taken from a monthly total return series for a representative set of stocks followed by the International Finance Corporation in each emerging market. The data are taken from 1976 to 1992. Monthly volatilities are estimated from monthly returns. The first regression model is given by

$$R_t=\sum_{i=1}^{12}\alpha_i D_i+\sum_{i=1}^{12}\beta_i R_{t-1}+\varepsilon_t$$

where R_t is the stock return during month t, D_i is the 12 monthly dummies to allow for different monthly means and R_{t-i} is lagged returns. If $|\varepsilon_t|$ is an estimate of the standard deviation of the stock market return for month t, stock price volatility is formed by the following equation:

$$|\varepsilon_t|=\sum_{i=1}^{12}\gamma_i D_i+\sum_{i=1}^{12}\rho_i|\varepsilon_{t-i}|+u_t$$

Return volatility is used to measure stock price volatility. The first attempt is made to explain an observed change in stock price volatility following opening up of markets. No correlation is found. Another attempt is made to estimate domestic price volatility to world market volatility and the impact of market opening on domestic stock price volatility. The following regression is run:

$$|\varepsilon_{st}| = \delta_0 + \delta_1 \text{Open} + \delta_2|\varepsilon_{wld}| + \delta_3|\varepsilon_{wld}|^*\text{Open}$$

using OLS. The dependent variable is the individual country's stock price volatility and the independent variables are the Open dummy (set to 0 if the month is before the opening month, and 1 otherwise), world volatility of the stock price index taken from the Financial Times Actuarial Index, and an interaction term between the domestic and world market volatilities due to stock market opening. An insignificant correlation is found between domestic stock price volatility and world stock price volatility. Domestic macroeconomic factors are captured by a recession dummy. It is set to 1 if the economy is in recession as determined by NBER and 0 otherwise. The recession dummy captures a decline in GNP, employment and industrial production. Stock market volatility is found to be positively influenced by the recession dummy.

This regression is run on 16 countries[2]. The only coefficient that shows any significance is that of the intercept. The highest R^2 for this regression is

[2] Argentina, Brazil, Chile, Colombia, Greece, Jordan, Korea, Malaysia, Mexico, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela.

.374 for Mexico.

Their last regression is $|\varepsilon_{st}| = \theta_0 + \theta_1 \text{Open} + \theta_2|\varepsilon_{ip}|$ where ε_{st} is defined as before and ε_{ip}= average volatility of industrial production for six months following month t. They do not find the coefficient of the volatility of industrial production to have a significant correlation with domestic stock price volatility for any of the eleven countries tested.

This paper is particularly helpful in guaging the explanatory power of regressions run on these countries run thus far. The results on the sixteen countries suggest that obtaining an R^2 of more than .50 on a model is good. These authors do not get any R^2 higher than that for the countries tested. It also suggests that a dummy variable for liberalization of markets does not add much explanatory power to the model and should be avoided as a right-hand variable.

Schachmurove (1995)

Schachmurove (1995) discusses the increased international investment in emerging markets characterized by the late 1980's. The emerging markets listed are Argentina, Brazil, Chile, Mexico, Korea, Philippines, India, Indonesia, Greece, Portugal, Taiwan, Turkey, Nigeria and Zimbabwe. The author describes these emerging markets as thin and narrow markets driven by poorly informed individuals rather than "market fundamentals". As an example of this lack of market fundamentals, only the following markets are cited as having accounting standards: Brazil, Chile, Mexico, India, South Korea and the Philippines.

Emerging markets show a convergence of national markets and an increase in correlations among stock markets during high volatility. The oil shocks of the 1970's and the 1987 crash are given as examples. The convergence of national markets is attributed to increasing intra-regional trade and expanding links between national economies (although no examples of these links are given). On the subject of portfolio investment, "explosive growth in cross-border portfolio investment" is cited as another reason for convergence in national markets made stronger since the experts directing those funds are all increasingly using the same information or have access to these same sources of information. The argument is that since there is a proliferation of similar data bases or similar sources in the investment world, there will be a convergence in the decision-making process.

This paper addresses the interdependency of emerging markets, what he calls the dynamic linkages of emerging markets. By calling the linkages "dynamic" it implies that there can be change over time (as in finding a dynamic path) and the extent to which an influential market, such as the U.S., can affect markets such as in Latin America. Furthermore, this working paper describes methods such as Vector Autoregression that are used to estimate interdependencies between emerging markets and the U.S. market in the present study.

The first point brought out is that global diversification has been attractive to a portfolio with returns from emerging markets as well as developed markets because the correlation between the two groups has been weak. To a U.S. investor, a portfolio with a broad global mix is believed to pay a higher return than one only containing U.S. stocks while reducing overall risk. Citing this lack of correlation as a starting premise, it is an interesting prospect then to examine the nature of interdependency between markets.

The author feels the contribution of this study is that it is the first to examine interdependencies across national indices. The newly emerging markets of Argentina, Brazil, Chile and Mexico are chosen for examination.

The Vector Autoregressive Model (VAR) is chosen for econometric specification. It addresses the interdependence between markets as revealed through the correlation of the disturbance term ε_t across countries. The author chooses the VAR because it provides identification of the responses to shocks originating in different stock markets. The point made is that if markets do not behave as a single regional market, the investor can take advantage of the benefits from diversification.

This paper elucidates the concepts of shocks and volatility. A shock to the market can be the result of a bad crop in Brazil, a military coup to the government or an oil shock. Volatility can similarly be caused by any of these supply or demand factors. Since this concept is unidentified conceptually, the way to identify it econometrically is through the error term of the regression. The error term is a way to capture whatever might be the shock. Model specifications such as GARCH or the VAR are ways to increase the precision of that error term for purposes of forecasting and prediction.

The vector autoregression is written as 1) $Y(t) = C + \Sigma\ A(s)\cdot Y(t\text{-}s) + e(t)$. Σ is a summation of 1 to L, the number of lags in the VAR. Y(t) is a $n\cdot 1$ vector of daily rates of return of the stock markets, C is a $n\cdot 1$ vector of constants, A(s) represents $n\cdot n$ matrices of coefficients and e(t) is a $n\cdot 1$ column vector of forecast errors of the best linear predictor of Y(t) using all past Y(s). Since e(t) is a function of Y(t), it is specified as uncorrelated with all the past Y(s). Moreoever, e(t) is also a linear combination of current and past Y(t), making e(t) serially uncorrelated. Each element of the e(t) vector, however, can be contemporaneously correlated.

Each component of A(s) measures the direct effect that a change in the return to one market has on another. The i,j-th component, for example, measures the direct effect that a change in the return to the jth market , say the U.S. market, would have on the ith market, say the Chilean market. The right hand side of each equation includes the same regressors, a constant, lagged values of each variable and an error term. That makes the estimation relatively straight forward.

Such a system of equations contains complicated feedback restrictions that estimate the interdependencies of interest. The approach of Sims (1980) traces out the moving average representation (MAR) analyzing the response (or reaction) of the system of equations to typical random shocks. The MAR is said always to exist and that it can be derived by successive substitutions on the right-hand side of $Y(t) = C + \Sigma A(s)\, Y(t-s) + e(t)$ to yield the new equation:

2) $Y(t) = \Sigma B(s)\, e(t-s)$ where the summation is from $s=0$ to infinity and

the n·n matrix of coefficients B(s) is derived from $Y(t) = C + \Sigma A(s)\, Y(t-s) + e(t)$. Equation 2) expresses Y(t) as a linear combination of current and past one-step ahead forecast errors or innovations. e(t) is therefore equal to Y(t) minus the best linear projections of Y(t) on all past values of the vectors Y(t-s). In B(s), for example, each i,j-th element gives the response of the ith market in s periods after a unit random shock in the jth market and none in other markets. Each response is conditional on the information available at time t. Through these responses, each element in vector e(t) can be contemporaneously correlated.

The results of the paper include the following. The block F-test or Granger-Causality tests indicate whether one variable, for example, the return in the Mexican stock exchange, helps forecast the stock market return of the Argentinean stock exchange one-step ahead. The markets that are affected by their own lags are the Argentinean, Mexican and the Chilean. The Brazilian stock market is affected both by its own lagged values and by the Argentinean market. Based on these block F-tests, it seems that the most influential market is the Argentinean market which affects the Brazilian stock market by helping to forecast the Brazilian stock market return.

Mullin (1993)

Mullin (1993) examines return volatility in Latin America. The volatility of emerging market equities is defined as the standard deviation of these equities. This article is relevant for appropriate explanatory variables of stock price volatility. The standard deviation of stock returns is taken as a measure of this return volatility. The topic of return volatility arises because emerging markets have attracted investors since the return performance has been high. Emerging equity markets have tended to be characterized by greater volatility than their developed country counterparts. The study uses data from 1976 to 1991 to examine return volatility in emerging markets. The emerging markets examined are Argentina, Brazil, Chile, Malaysia, Mexico, South Korea, Taiwan, and Thailand.

The evidence on return volatility indicates that this volatility reflects the volatility of economic conditions such as inflation rates and real exchange rate changes. A CAPM model is used to model the measure of risk in developing country equity returns. Using beta as a measure of risk, a yearly measure is taken. The data indicate that developing country equity returns are more closely related to yearly measures of covariance risk than to monthly measures of risk.

The study cites the economics of return volatility. The stylized facts are that many developing-country indices have exhibited high levels of high return variance relative to developed market indices. One reason given for this return variance is that trading within a market is concentrated among a small handful of issues. In Mexico, for example, the stock of Telemex accounted for 17 percent of domestic capitalization. In Argentina, the stock of Telefonica of Argentina accounted for 18.5 percent for that country's domestic capitalization. This is in contrast to the United States, where Exxon, the most highly capitalized stock in the market, accounts for only 2.6 percent of the total market capitalization in 1991. In the paper it is the highest for Latin American countries and Taiwan. Argentina has the highest concentration.

A number of factors are associated with this return volatility. The first is unstable monetary policies. Unanticipated monetary shocks tend to increase the covariance between the rate of exchange rate depreciation and returns in local currencies. Theoretically, unanticipated monetary shocks would decrease interest rates and increase the local currency returns when real shocks predominate. Rapid monetary expansion, for example, leads to high and volatile rates of inflation. The second is exchange rate policies.

Mexico and Argentina are cited as two countries who tried to restore real exchange rate competitiveness by implementing large nominal exchange rate devaluations which led to real exchange volatility. Real exchange rate volatility implies risk of investing in firms whose relative input and product prices fluctuate with the real exchange rate.

A third relationship investigated is the relationship between market concentration and volatility. A positive relationship would be expected since less diversified portfolios tend to be more volatile. The relationship is found to be positive and statistically significant for the countries in the sample.

The implication of these relationships for international investors is that emerging market stocks are considered to offer diversification benefits because they have been found to be lowly correlated with developed country stocks. This article touches on the macroeconomic factors that are correlated with stock return volatility.

Other Relevant Papers

Divecha, Drach and Stefek (1992) take a quantitative approach to emerging markets. An emerging market (EM) here is defined by the Morgan

Stanley Capital International Indices or the Financial Times World Index[3] as one which has securities that trade in a public market and is not a developed market. As a market, it has a reliable source of data and is of interest to global institutional investors. EMs are found to be more volatile than developed markets and are not highly correlated with each other or with developed markets. The portfolio risk is therefore lower for the global investor in these markets.

The stock returns from EMs tend to be more homogeneous than in developed markets implying that a strong market force dominates other factors. While correlation does not appear to be present, there does seem to be some outside force that causes the stocks of these different countries to follow the market's movements.

A model is constructed to analyze risk and return in emerging markets. It is a multi-factor model that decomposes portfolio return into various components. The focus is on the excess return or return beyond the risk-free rate. The excess return is broken down into currency return and excess return is further broken down into country factor return, returns accruing to salient

[3] Argentina, Brazil, Chile, Colombia, Greece, Hong Kong, India, Indonesia, Japan, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Singapore, Taiwan, Thailand, Venezuela, Zimbabwe.

attributes of companies or industry return and returns such as price/earnings ratios.

The return to global portfolio depends on the home country of the investor. The excess return to an investment abroad is the product of the return of the investment in its local market, $1 + r_i$, and the exchange return, $1+r_x$. The model used is one of risk and excess return or return beyond the risk-free rate. Its data are currency returns and excess returns earned in local markets.

The model's main formula is

(1) Excess numéraire return= $(r_x + r_{tl} - r_t) - (r_l - r_{tl}) + (r_x \times r_l)$

The first term is Currency Return, reflecting both exchange return and the differential in interest rates between countries. Subtracted from it is Local Excess Return, excess return of the investments in the local market. The third term is a Cross-Product between the exchange rate and the local currency return. The cross product term is important for countries in which there are huge swings in exchange rates such as Argentina or Brazil, whereas not as important for countries such as Taiwan or South Korea where this is not the case.

The model for monthly local excess return is: (2) Local Excess =

Country Factor + Industry Factor + Risk Index Factor + Specific Return. Each asset is assigned to exactly one of 36 industry categories. Risk indices include: success; yield; variability in markets; earnings-to-price ratio; book-to-price ratio; and liquidity. The component of the variance that is explained in EMs is greater than in the developed countries.

As stated earlier, the significant implication of the results is that a single market force seems to have a large impact on the movement of stock prices in these markets. Trade links between these emerging markets is one explanation for a market force, and common country investment restrictions is another. Markets are well-diversified across industries. Industry differentials are overwhelmed by the dominant market force although correlations are low in general. EM stocks are desirable because of their apparent predictability. The implication for the portfolio manager is that risk reduction is possible because of this low correlation between EMs and developed markets. There is a diversification opportunity despite this dominant market force that causes the stocks to move together. The stocks are not correlated with each other.

Speidell and Sappenfield (1992) present a description of the global market for investing rather than an actual model. They describe covariance risk and the role of emerging markets.

The global market for EM returns is characterized by higher risk and return than the developed markets. They find a correlation risk between these returns is considered bad because more decisions will be made by fewer players. The risk is when seemingly diversified portfolios could prove to be undiversified in the future because its assets will move uniformly rather than independently. The assets begin to move together instead of independently. Concern about this increased correlation is given for the following reasons. The first is that institutional portfolios represent a large portion of trading. First, the practice of indexing tends to bind stocks together. Equity portfolios in the U.S. represent over 50% of assets for some institutions with similar index funds growing abroad. There is a high likelihood that trading signals will affect all these portfolios simultaneously. Large decisions, such as buying and selling, drive stocks in an index together regardless of the merits of each individual member.

Second, the Common Market links the returns of European countries. Increased integration of fiscal and monetary policies is likely which increases correlation risk. Unifying trade zones could develop in Asia and the Americas, such as the North American Free Trade Act.

Finally, "global" events, as opposed to local events, are likely to occur more frequently. The growth of world trade increases interdependence between companies. Moreover, the advance of instantaneous communications means that markets respond simultaneously to global news. It all adds up to greater interdependence and hence correlation risk.

This correlation can be eliminated by manipulating weighting of the returns. Once expected excess return is higher than a certain percentage, changes in return can influence changes in correlation to minimize the latter.

These results are in contrast contrast to Divecha et al. who said that correlation in EMs did not appear to exist. One reason for this discrepancy could be the choice of countries as emerging markets in each study. Divecha et al. classify Hong Kong, Singapore and Japan (over -the-counter) as emerging markets, for example, whereas Speidell and Sappenfield do not.

Hauser, Marcus, and Yaari (1994) start from the premise of low correlation between stock returns of developed and emerging markets. This is an advantage as expressed in terms of a risk/return tradeoff. They examine the role of exchange rate risk in determining the benefits of international diversification. In developed markets, exchange rate risk can be hedged, i.e. sold for future delivery to protect against a declining market price over the specified time of buying and selling to enhance benefits of diversification. In emerging markets, by contrast, hedging currency risk of high-risk EMs can decrease the gains from this international diversification.

The emergence of capital markets in Latin America and Far East Asia is part of the globalization of capital markets. An attempt has been made to create security markets compatible with those of developed markets. A low correlation between EM and developed returns makes the risk/return tradeoff favorable. The benefit from hedging depends on the contribution of currency risk to the overall volatility as measured by the variance of stock return. The variance of monthly returns is decomposed into a component capturing the variance of the change in return and a component capturing the variance in change in foreign currency and the covariance between the two. The volatility in the developed countries returns is found to be largely due to exchange rate risk where hedging currency risk enhances the performance of a well-diversified portfolio. The currency risk offsets the effect that international diversification has to reduce risk.

The EM returns show that a negative covariance between changes in stock produces a decreased stock volatility in terms of dollars. Emerging markets are often plagued by high and volatile rates of inflation. The higher rates of inflation induce higher nominal rates of returns on stocks, in the local currency, but also higher rates of depreciation of local currencies relative to the dollar. The net effect is that an American investing in emerging foreign markets is faced with a lower volatility than domestic investors in those markets. The two offsetting changes of higher nominal rates of return and higher depreciation of the local currencies create a partial insurance in dollar terms for the American investor.

A display of the performance of well-diversified EM portfolios shows that unhedged portfolios generally perform better than hedged ones. Hedging currency risk, therefore, does not enhance portfolio performance as it does with the developed markets. Second, the overall risk in emerging markets is considerably higher than that in developed markets. This higher risk in price volatility is attributed to reduced liquidity in emerging markets. In emerging markets, it is of the order of 22% to 130% in contrast to 9% to 35% in the developed markets. They consider the optimal proportion of investment in emerging markets 10-15%, but today global investors allocate less than 1% of their funds to those markets.

Errunza (1994) asserts that a foreign investor would improve performance as well as reduce risk by including EMs in his or her portfolio. The study cites Levy and Sarnat (1970) as one of the earliest to suggest substantial benefits from investing in developing countries, using local market indices for 1951-1967 published by the International Monetary Fund. Other studies since then have found benefits to EM diversification using methods of efficient frontiers, factor analysis and asset pricing models. There is evidence of the benefits of EM diversification over the last twenty years for different sets of markets, varying time periods, many types of data and sources, and different methodologies. In particular, the major findings over the period 1960 to 1990 are the following. The first is that EM diversification would be beneficial in terms of both increased returns and reduced risk. The second is that the domestic systematic risk has been higher than larger developed markets but not necessarily higher than the smaller developed markets. The third is that the return correlations vis-à-vis developed markets have been low. Between emerging markets, the correlation has been negligible.

An issue directly addressed is whether riskiness in EMs is higher than in developed market returns. Using standard deviation of market index as a measure of riskiness, EM returns show a higher risk. That measure, however, is not considered a good measure of risk. More appropriate measures of risk are relative riskiness of individual cross-national assets in a similar risk class, i.e., industry and the contribution of the security to the risk of the investor's portfolio.

A point brought out was that country selection is more important than stock picking because stocks from a given market tend to move together. The country factor therefore dominates world, currency, and industry influences in the case of the EMs. This leads to some discussion of individual country conditions. Capital market integration does not necessarily imply high correlations. Recent economic reforms, financial liberalization and privatization policies pursued by many EMs will impact their industrial organization, internal competition and corporate structures. It is difficult to assess how this will affect future return correlations although composition and performance of market portfolio will be affected.

Furthermore, it is impossible to predict the impact of global phenomena such as liberalization of international trade, trading blocks and the future of the European monetary union. As suggested by Speidell and Sappenfield, correlations need not increase if a fund sold is offset by a fund bought. As a result, the long-run path of return correlations is unpredictable. The potential for diversifying stocks in these markets is still positive. Errunza and Losq (1985) examine pricing and portfolio implications of investment barriers in the context of international capital markets.

The paper has the following characteristics. First, it uses the concept of risk, conditional market risk. This form has a closed-form solution that can be found for the equilibrium risk-return tradeoff in segmented markets. Securities are inaccessible to a subset of investors that command a "super" risk premium that is proportional to the conditional market risk. Second, the model lends itself to the analysis to an intermediate market structure, not just the polar cases of complete integration and segmentation respectively. This is considered an improvement because tests of the polar cases have led to inconclusive results. Although formal statistical procedures test the null hypothesis of market integration or segmentaion against the alternative of segmentation or integration, the rejection of the null has been interpreted as evidence of the alternative hypothesis of segmentation. Joint tests of the market structure hypothesis with the mean-variance paradigm could conceivably reject integration in situations where capital markets are truly markets; if it is priced to an APT-type model, for example, or if the market structure does not conform to either polar cases. This model allows for mild segmentation.

The model has the following assumptions for an international capital market. The first is that access to securities is unequal. Investors are restricted and unrestricted. The restricted investors can only trade in a subset of securities. The second is that capital markets are perfect. National capital markets are frictionless with no taxes nor transaction costs. The third is the mean-variance assumption. The expected utility of each investor can be represented as a function of the expected value and the variance of the real returns on the investment portfolio. The fourth is that each investor can freely lend and borrow at the same real rate of interest. The fifth is that real returns are assumed to be normally distributed.

The test of mild segmentation hypothesis is that if markets are fully integrated, then the risk (World beta) adjusted average return should be similar across national markets. The study uses the following countries in its sample: Argentina, Brazil, Chile, Greece, India, Korea, Mexico, Thailand, Zimbabwe and the U.S. Countries whose securities are considered to be part of the eligible set are the U.S., Thailand, Zimbabwe, and Mexico's open firms. Countries whose securities are considered to ineligible are Argentina, Brazil, Chile, Greece, India, Korea, and Mexico (other than open firms). Some securities from Thailand and Zimbabwe fall into this category as well.

Cross-sectional regresssions are used to capture the degree of effective segmentation in the international capital market. Under mild segmentation, the following predictions are made regarding risk, return, and portfolio composition. The first is that eligible securities are priced as if the market were not segmentated. This arises because no security is in excess supply or in excess demand. The second is that the ineligible securities command a super risk premium which is proportional to the conditional market risk. The third and fourth are the specific nature of the portfolios held by unrestricted and restricted investors respectively.

The interpretations of these predictions are the following. As a result of segmentation, the restricted investors cannot hold the ineligible securities and properly diversify their holdings. As a second best solution, these restricted investors hold market portfolio of eligible securities plus a proxy for the market portfolio of ineligible securities, the portfolio DP (diversified portfolio), supplied to them by the unrestricted investors. The unrestricted investors act, therefore, as financial intermediaries. They provide diversification services for which they receive an implicit renumeration. They supply securities for which there are securities with a comparatively low return.

In the absence of super risk premiums, the expected excess return on any security would be proportional to its covariance with the world market portfolio. Since by hypothesis, the restricted investors cannot hold the ineligible securities, these would be in excess supply. Consequently, for equilibrium to prevail, super risk premiums must exist so that unrestricted investors are induced to acquire the residual fraction æ of MPIS (Market Portfolio of Ineligible Securities) and supply the same fraction æ of the diversified portfolio, DP.

The super risk premium for the market portfolio provides a measure of the increase in required return which ineligible securities must yield because of the segmented nature of the market. The super risk premium can be interpreted to measure the effect of segmentation on the cost of supplying risk securities in the ineligible segment of the market. The effect of market segmentation becomes more pronounced as the risk aversion of the unrestricted investors increases and as the correlation between the two segments of the market decreases.

The testable hypothesis includes the following components: 1) the unconditional market risk of any security is proportional to its beta coefficient and 2) the conditional market risk of any ineligible security is a linear function of the β and γ coefficients 3) specifications of risk-return tradeoff for eligible and ineligible segments respectively. A two-factor return generating model is specified. The covariability of returns between eligible and ineligible securities are severely limited; industry effects, for example, are simply assumed away.

Since the residuals were heteroscedastic, their results are of cross-sectional regressions using Generalized Least Squares (GLS) parameter estimates. The parameter estimates and their significance are similar across the two portfolio construction procedures of ineligible and eligible securities.

The distinguishing feature of this model is that the unequal access assumption approximates the reality of a mildly segmented world market. The incidence of mild segmentation does not affect required return on an eligible security. The required return on an ineligible security, however, is different from what the standard CAPM would predict. These securities command a super risk premium.

Errunza, Losq and Padmanabhan (1992) find that the world market is neither fully integrated nor completely segmented as defined by the market for securities as an international asset pricing model. The integration hypothesis is the joint hypothesis that markets are efficient. The segmentation hypothesis is that markets are inefficient, but it is not as clearly defined as the integration hypothesis. Mild segmentation, however, postulates that a group of investors is restricted to trade only in a subset of securities while the unrestricted investors are open to trade in all securities in the market. The segmentation, therefore, lies in this restriction.

Return-generating processes and risk-return relationships are specified for complete integration and mild segmentation. Data range from 1975 to 1987 from Emerging Markets Data Base (EMDB) end-of-month prices; CRSP stock prices and dividends for all U.S. securities; and IFS exchange rates in U.S. dollars.

The eligible segment is proxied by U.S. securities and securities are classified within each EM as a set of ineligible securities. Thus each EM (Argentina or Brazil, for example) constitutes a separate ineligible segment. This is in contrast to Errunza and Losq (1985) in which they choose to pool securities across EMs and classify the entire set as ineligible securities. The advantage to this approach is that by investigating each market separately, their assumption of free portfolio flows between EMs is not needed. Given that it is an assumption of free movements among ineligible markets, this assumption is questionable. But for their purposes, it increases the sample size for cross-sectional tests.

A varying market structure is found for the eight emerging markets examined. The null hypothesis of complete integration is rejected in all eight cases. Mild segmentation characterizes the market for Brazil, Chile, Greece, Korea and Mexico. The markets for Argentina and Zimbabwe, on the other hand, have market structures somewhere between mild and complete segmentation. The market structure for India does not seem to fit any of the market structures described. These results are consistent with a priori expectations. As of 1984, portfolio flows for these countries followed the following pattern. In Brazil, Korea and Mexico, there were restrictions to special mutual funds. In Greece, Chile and Argentina, there was relatively free entry but some restrictions of repatriation of income, particularly in Argentina. Such restrictions took the form of requirement of registration of the income with or permission of the Central Bank, Ministry of Finance or an Office of Exchange Controls. Income is defined as dividends, interest, and realized capital gains. In Zimbabwe, entry is restricted by shares and the repatriation of income is also characterized as restricted. In India there is restriction by investor nationality but repatriation of income is free.

The study therefore illustrates the apparent diversity in market structure that characterizes emerging markets. This is important when examining issues such as predictability.

Bekaert and Harvey (1994) examine market integration in world markets by allowing integration to vary over time. Expected returns are described in countries which are segmented in one part of the sample and become integrated later in the sample. Their results suggest that a number of emerging markets exhibit this time-varying integration.

Markets are described as completely integrated if assets with the same risk have identical expected returns irrespective of the market. If a market is segmented from the rest of the world, however, its covariance with a common world factor may have little or no ability to explain its expected return. That market will be cut off from the common world factor and cannot consequently be influenced by it.

The contribution of this paper is that here market integration is allowed to change through time. Uptil this point, asset pricing studies have been classified as segmented markets, integrated markets, and partially segmented markets. Indeed, the well-known CAPM model assumes markets are segmented using one country's data.

This classification views world capital markets as perfectly integrated. Rejection of these models can be viewed as inefficiency in the market or rejection of market integration. Allowing market integration to change over time introduces more flexibility that is more relatistic. The mild segmentation models of Errunza, Losq and Padmanabhan allow an intermediate condition between full integration and segmentation repectively, but the degree of segmentation is fixed over time. The approach of Bekaert and Harvey moves a step further.

There are three sources of time-variation in expected returns: variation in the price of risk, (λ_{t-1}, λ_{it-1}); variation in the conditional risk measures (covariance with world and local market variances); and variation in the degree of market integration, $\phi_{i,t-1}$. There is evidence of predictable variation in returns. To gauge the ability of the model to capture the observed predictability of returns, the time tested is where disturbance e_t is orthogonal to information Z_{t-1} available at time t-1. A Wald test is used to test the joint significance of the coefficients of a linear regression of $e_{i,t}$ onto a set of information variables Z_{t-1}. It is useful to track the source of rejection if the model fails to replicate the observed time-variation of expected returns. The measure for market integration allows for regime probabilities to be modelled directly using the logit

form:

$$\phi_{i,t-1} = \frac{\exp(\gamma_i' Z_{t-1}')}{1 + \exp(\gamma_i' Z_{t-1}')}$$

γ_i is a vector of coefficients and it makes sense to condition the regime probabilities on local information variables.

The time-varying integration model is modelled using the generalized method of moments. The convenience of this method is that the dynamics of the conditional covariances and variances do not have to be explicitly modelled.

Variables included in the estimation are world price of risk, local price of risk and coefficients on each asset. Multiple sources of risk are incorporated into the framework to include foreign exchange risk. The expected return is a function of variables such as currency excess return for country i, world price of covariance risk and world price of foreign exchange rate risk. To avoid estimation that would involve an "intractable number of parameters"[4], local currency returns are computed against a trade-weighted basket of foreign currencies. The product of local currencies and the weight would represent the pricing of the different currencies. As a result, this model addresses the role of currency risk and market integration, considered an improvement over previous work.

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[4]Geert Bekaert and Campbell R. Harvey,"Time-Varying World Market Integration," Stanford and Duke Universities, Working Paper, May 24, 1994, 14.

The data used are the 21 developed markets from MSCI and 20 emerging markets from the IFC of the World Bank. The data for all returns, developed as well as emerging, begin in 1975 and end in 1992.

Emerging market returns show some differences from the developed market returns. They are characterized by high volatility, ranging from 18% to 104%; by contrast, the volatility of developed markets (MSCI) returns range from 15% to 42%. The emerging market returns also show a higher occurrence of autocorrelation than developed markets. Twelve out of 21 countries in the EM sample show first-order autocorrelation greater than 10%, in contrast to only five out of 18 of the developed countries. This evidence of autocorrelation suggests that the returns in many of these countries are, at least to some exent, predictable based on past returns alone.

The econometric model of predictability used is one in which the null hyothesis is that expected returns are constant. The total information set, Z, is comprised of local components, Z_i, and global components, Z. The global information variables include a constant, the world market dividend yield in excess of the 30-day Eurodollar rate, the default spread (Moody's Baa minus Aaa bond yields), the change in the term structure spread (U.S. 10-year bond yield minus 3-month U.S. bill) and the change in the 30-day Eurodollar rate.

These variables are designed to capture fluctuations in expectations of the international business cycle, acknowledging an 89% correlation between U.S. economic growth and G-7 economic growth.

The set of local information variables includes a constant, local equity returns, local exchange rate changes, local dividend yields and the ratio of equity market capitalization to GDP. A small degree of correlation between these local variables and global variables is acknowledged, but it is not considered large. It is considered analogous to the correlation between local economic growth and world economic growth.

The results are that the null hypothesis of constancy of expected returns is rejected at the 10% level for emerging markets and at the conventional level for developed markets.

The study examines five different countries: Chile, Colombia, Greece, Korea, and Nigeria. The results for Chile show signs of segmentation that is consistent with expectations. There are institutional barriers to investment such as currency controls and restrictions on capital repatriation.

The results for Colombia also suggest that the market is more segmented than integrated, consistent with the investment environment. It is one of the most illiquid among the emerging markets which combined with the presence of political risk has kept the market largely segmented.

The results for Greece are that it is integrated into world capital markets. As of 1990, its GDP per capita income exceeds the U.S. $2,200 level World Bank definition for emerging markets. Its investment environment has no foreign investment restrictions outside of industries such as banking, shipping, and insurance. This integration is therefore consistent with its investment environment.

The results for Korea are mixed. Its integration paramenter is high and it actually ceased to qualify as an emerging market in 1990 when its per capita GDP exceeded US $5,000. It, however, does have investment regulations such as on foreign participation in terms of ownership.

Foreigners, however, have access to the market through measures such as U.S. dollar- and non-U.S. dollar- denominated country funds. It is one way to allow foreign participation despite restrictions.

The results for Nigeria show signs of segmentation which is consistent with prior expectations. Liquidity is extremely thin and government approval is required for direct investment. The authors feel particularly pessimistic about its political situation.

Harvey (1994) describes the method of conditional asset allocation applied to emerging markets. The purpose of the study is to look at the impact of emerging equity markets on global strategies. Traditionally, models of unconditional asset allocation have been used to compare developed and emerging markets to each other. This paper departs from that approach by using a method conditional on preceding information that relates to the predictability of returns. The implication of this approach is that forecasting models can be developed so that the model can incorporate this previous information that was not possible before.

Since this method is a departure from the method of unconditional asset allocation, a brief explanation of this unconditional approach is in order. A better understanding of this departure would result. The method is considered unconditional because of the way the expected returns, variances and covariances are chosen. Expected returns are the mean returns over the previous five years (or 60 months) and the best forecast of the equity return is assumed to be its past average. The expected returns follow a pattern similar to a random walk with a drift. The model implies that there is no other information relevant for forecasting next month's stock price other than its previous price, and hence, stock returns are not predictable.

The restriction on inputs is that the variances and covariances cannot move in complex ways. The only way for the manager to obtain an efficient portfolio (highest expected return for a level of volatility) is to hold investment weights implied by the actual data. Knowledge of the data, however, is usually not possible.

By contrast, conditional asset allocation uses forecasts rather than actual data to manage its efficient portfolio. The forecasts are of expected returns, variances and covariances. Linear regression models are built for the conditional means using information variables. Conditional covariance is the forecasted value of the product of the residuals for the regression models for asset i and asset j.

The paper uses data on emerging markets for the criterion IFC investibles[5]. The sample period is 1976.01-1992.06 with a subsample of 1985.01 to 1992.06. The display is of U.S. dollars returns and local currency returns. At a glance, the mean U.S. dollar returns for emerging markets range from 72% (Argentina) to -6% (Indonesia). By contrast, the corresponding range for developed countries is 25% (Hong Kong) to 10% (Finland). There seem to be higher returns among EMs than among

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[5] Argentina, Brazil, Chile, Colombia, Greece, India, Indonesia, Jordan, Korea, Malaysia, Mexico, Nigeria, Pakistan, Philippines, Portugal, Taiwan, Thailand, Turkey, Venezuela, Zimbabwe.

developed countries.

The geometric average reflects the average returns to a buy-and- hold strategy. In high volatility, there could be large differences in arithmetic and geometric mean returns. As such, EM stocks are characterized by high volatility.

The predictability of these returns has bearing on the forecasting ability of the conditional moments that are used in this subsequent model and is an advantage to investing in the EM assets if predictability exists. Of the 21 developed countries tested, 14 show significant predictability. Moreover, a multivariate test of the predictability suggests that the hypothesis that expected returns are constant can be rejected at the 99% level of confidence.

Regression models show that the returns in a number of emerging markets are predictable based on both global and country-specific information variables. When regression forecasts are combined with a portfolio optimizer, simulated portfolio performances improve.

There are at least two issues, however, not dealt with in the study. The first is the source of predictability in EM returns that could be an investment advantage. The second is the extent to which these markets are integrated into world capital markets. The description given by Errunza et al. (1992)

asserts that as long as the emerging market asset is investable, the portfolio manager may not be concerned whether the market is integrated. Lack of integration could actually present opportunities for investors: High expected return assets could be purchased at prices cheaper than comparable assets in developed countries. The results of the study indicate that there is a benefit to including emerging market assets in a globally diversified portfolio.

The conditional-mean-variance frontiers test use data from 1980.12 to 1992.06. The conditional covariance is the forecasted value of the product of the residuals for the regressions for asset i and j. The portfolio frontier is taken from the values of the variance-covariance matrix:

(5) $\mathrm{Cov}\,(r_{it}, r_{jt}\,|Z_{t-1})=E(\varepsilon_{it}|\,\varepsilon_{jt})$

where r is the return on country i and j respectively and Z is a 1 x l vector of global and country-specific information variables known at time t-1.

The mean-variance problem is the same as in the unconditional case, i.e. optimizing expected returns subject to risk measure by standard deviation. A linear model is used for conditional means and forecasting variables include a constant as well as world variables such as the lagged world dividend yield, lagged world returns, and country-specific variables.

The results are the following. Using EM 1986-1992 data with the mean-variance problem, the frontier flattens out and moves to the lower standard deviation range. The investment weight assigned to EMs increases through time. When there is a 20% cap on EMs, the constraint is binding from 1981. Beginning in 1986, there is a reweighting to emerging markets. The EMs included cause volatility to decline and mean return to increase. When included in the table of portfolio strategies, higher expected returns can be gained at lower volatility.

The regression results demonstrate that the average historical mean is not a very good forecast of the expected returns of most countries. As a result, the conditional asset allocation method calculates forecasts on an out-of-sample basis for its regressions assuming fixed coefficients through the entire sample. In sum, the main benefit of investing in EMs comes from the predictability of the EM market returns. Predictability enhances portfolio performance.

The goal of the Harvey study is to examine the impact of emerging equity markets on global investment strategies given an apparent low correlation within EMs and developed markets respectively. Harvey starts from the position that low correlation between emerging equity returns and developed market returns has been documented. Concerning active portfolio strategy, this means that the opportunity set is becoming larger with the inclusion of EMs. Higher expected returns can be gained at lower volatility. Harvey presents portfolio simulations that verify that the low correlations within EMs and with developed markets respectively produce superior out-of-sample portfolio allocation and indicate that the portfolio programs produce weights that are ex post (perfect foresight) optimal. Moreover, strategies that included emerging equity markets have consistently outperformed markets. But there is no guarantee that these weights will work with data outside the portfolio program providing further evidence of this low correlation.

Harvey (1989) also provides more background about conditional asset pricing models. For example, conditional covariances are used in contrast to unconditional models such as CAPM or some models that allow the assets' "betas" to be stationary over a fixed period. The tests of asset pricing models at the conditional level allow for expected returns to vary over time and assume that conditional covariances are constant. This paper proposes tests of the CAPM and multifactor asset pricing models that allow for time-varying expected returns and conditional covariances.

The methodology of the paper includes the following. The first form of the test is a CAPM with constant reward to variability. The expected return on asset j is a function of the covariance between returns on assets j and m multiplied by a constant λ. The constant λ represents the ratio of the conditionally expected return on the market portfolio divided by the conditional variance of the market. The coefficient λ represents the compensation the investor must receive for a unit increase in the variance of the market return. It is constant in terms of a market-wide portfolio, not an individual asset.

The three tests presented in this section are based on the errors. The first test includes λ coefficients that only apply to the market portfolio, not individual assets. The second includes asset-specific λ coefficients, not done in the first test. The third includes an asset-specific intercept, not done in the first test and does not include asset-specific λ coefficients, done in the second test.

The second form is the multifactor model with constant reward to volatility. This allows for time-varying covariances, returns and volatilities. A point made is that in such a specification it is difficult to interpret the rejection of the model. The model may be an adequate description of the data but the assumption of a constant parameter may be incorrect.

The data range from September 1941 to December 1987. Asset return data come from the University of Chicago in monthly stock portfolio deciles. The information set includes the first lag of the excess return on equally-weighted NYSE portfolio, the junk bond premium, a dividend yield measure and a term premium. Mean returns are ranked from the smallest decile portfolio to the largest portfolio on total firm value. The highest first-order autocorrelations are found with the mid- to smallest deciles.

The results of the time-varying conditional covariances are the following. The null hypothesis is that the conditional covariances are constant. There is strong evidence rejecting the null. The R^2's indicate that the covariances are time-varying and predictable.

The contribution of this paper is that it provides a way to test CAPM that allows for both time-varying expected returns and time-varying conditional covariances. The results indicate that conditional covariances do change though time. Models are estimated holding the expected excess return on the market divided by the variance of the market constant. High returns are associated with high conditional covariances. This is consistent with the asset-pricing model. Further, there is evidence that reward-to-risk ratio is time-varying.

Conclusion

This literature review has described other work done on either the emerging markets or a developed market relevant to emerging markets. The first section described the most pertinent papers for the present study. The first three papers elucidated the econometrics of stock price volatility in emerging markets. The second three gave examples of studies that deal with emerging markets in particular. They are helpful in determining the variables that could explain stock price volatility.

The second section described other papers on emerging markets or on developed markets which relate to emerging markets. They provide an idea of the tasks faced and how some obstacles have been overcome. The next task is to investigate the determinants of changes in stock price volatility.

Chapter 3

The Estimation of Stock Price Volatility

Introduction

This chapter examines how the volatility of a spot rate of stock price is computed. We begin with some background from the econometric and finance literature. Engle (1982) is one study in which an econometric method is offered to model stock price volatility with this type of financial time series data. As described in the literature review, empirical work using time-series data frequently adopts ad hoc methods to measure and allow shifts in the variance over time. Engle has identified the ARCH process which produces fatter tails than the normal density distribution; financial data residuals tend to follow this fat-tailed distribution. The ARCH estimation produces a variance that is conditional on past values of the variance. As described in the literature review, assuming that the error term ε_t follows an ARCH process has improved forecasting ability over assuming that ε_t is generated by a process whose mean and variance do not change over time.

Context

This study applies a well-known econometric method to the new set of emerging markets data. One observation in the literature is that stock price data are prone to heteroscedasticity. As discussed in Chapter 2, the data residuals are found to cluster over time making them heavy-tailed or follow a leptokurtic trend. Engle maintains that forecast intervals improve if "additional information from the past were allowed to affect the forecast variance"[6]. He models the variance of the error term, ε_t, as a function of its past errors. The variance is recognized to change over time and volatility is measured as a variance conditional on past variances. Bollerslev extends the ARCH model to the more general case of GARCH (Generalized ARCH) which is analogous to the generalization from AR to ARMA. It allows a memory term δ_i to enter the function of the variance.

This extension comes from the need to model an ARCH process which allows a more flexible lag structure to allow for a learning mechanism. In the ARCH(q) process, the conditional variance is constructed as a linear function of past errors only. In a GARCH(p,q) process, the p stands for the order of

[6] Robert Engle, "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," Econometrica, vol. 50, No. 4 (July, 1982), 988.

the coefficients of the lagged dependent variable σ_t^2's in the function $\sigma_t^2=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\alpha_2\varepsilon_{t-2}^2+\alpha_q\varepsilon_{t-q}^2+..\delta_1\sigma_{t-1}^2+\delta_2\sigma_{t-2}^2+..\delta_p\sigma_{t-p}^2$ .The q stands for the order of the coefficients on the lagged error terms in the same equation.

The information set that conditions the distribution of the disturbance is ψ_t. It is defined as all information available through time t, or can be interpreted as ε_t. In a GARCH(p,q) process, lagged values of the variances are allowed in the conditional variance. The conditional variance is a measure of the forecast error between one period and the next. The inclusion of the lagged conditional variance values, as opposed to a linear function of past sample variances, is that the former includes this memory process that corresponds to a learning process. The errors from time t-5th period can reduce those of the t-4th period. By contrast, in the ARCH case, this learning is less likely. Sample variances do not include previous period's mistakes. The same errors will be repeated. Learning cannot take place as easily.

The precise nature of the stock price prediction error is the reason that the conditional variance has been chosen to measure the stock price volatility. As described in DeSantis and Imrohoroglu (1994), the current volatility, as estimated from the GARCH(1,1) parametrization, depends on two things: past squared innovations and an autoregressive component of the GARCH process. The estimation of the variance captures the heteroscedastic component from the innovations and the autoregressive component captures the presence of autocorrelation in tl errors.

In this study, the Exponential GARCH (1,1) method is used to estimate the conditional variance that represents stock price volatility. Once the standard deviation of the conditional variance is computed, it is used as a dependent variable. A model such as GARCH is useful when the OLS method of estimation does not suffice. The GARCH model accounts for the heteroscedasticity and autocorrelation that the OLS model does not.

The GARCH specification of conditional variance is justified for two econometric reasons. First, the GARCH model is a specification for data such as stock price data that are leptokurtic or fat-tailed in their residuals. The data of stock price residuals in this study show a similar pattern of being fat-tailed. Second, the ARCH and GARCH models have shown greater predictive power for the forecast variance than other methods which either produce an infinite unconditional variance or require specification of the causes of a changing variance.

Engle and Bollerslev identify the autoregressive process $y_t = \gamma y_{t-1} + \varepsilon_t$ and the function $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \varepsilon_{t-2}^2 + \alpha_q \varepsilon_{t-q}^2 + .. \delta_1 \sigma_{t-1}^2 + \delta_2 \sigma_{t-2}^2 + ... \delta_p \sigma_{t-p}^2$ to compute the conditional variance. As described in the literature review, the equations for the GARCH (1,1) process are

1) $\varepsilon_t \mid \psi_{t-1} \sim N(0,h_t)$ where $\psi_{t-1}=\varepsilon_{t-1}$

2) $h_t=\alpha_0+\alpha_1\varepsilon_{t-1}^2+\delta_1 h_{t-1}$

DeSantis and Imrohoroglu (1994) apply the GARCH (1,1) method to emerging markets to the extent relevant to this study.

The method is the following. A random variable of stock price, P_t, is drawn from the conditional density function $f\,(P_t|\,P_{t-1})$ in which the forecast of today's value is based upon past information of that price. Under standard assumptions, the forecast of today's value is simply $E(P_t\,|P_{t-1})$. Today's forecast depends upon the value of the conditioning variable P_{t-1}. The variance of a one-period forecast is given by $V(P_t|\,P_{t-1})$. The expression is written recognizing that the conditional variance depends upon past information and therefore is a random variable.

The conditional variance is central to the GARCH specification. It is computed conditional on the past information set comprised of past values of the variances of P_t , the stock price. Modeling the conditional variance as the stock price volatility is therefore the focus of this study. As defined above, it estimates the nature of the prediction error to the forecast of the model. The kind of conditional variance of interest is when it can be used as a dependent variable. The question is whether the conditional variance can be explained by right-hand explanatory variables in a Yule-Walker model.

The GARCH model accounts for fat-tailed distribution of the error term. Heteroscedasticity causes the clustering of the error terms that leads to the fat-tailed distribution. Heteroscedasticity is corrected through maximum likelihood Generalized Least Squares nonlinear estimation and autocorrelation through transforming variables to difference out the autocorrelation between the error terms.

Estimating Stock Price Volatility

To compute the conditional variance, the assumptions of the GARCH model are the following, identical to the ARCH(1) model:

$$y_t = \beta' x_t + \varepsilon_t \qquad \varepsilon_t | \varepsilon_{t-1} \sim N(0,\sigma^2)$$

The disturbance of the above model is conditioned on an information set at time t, denoted by ψ_t. The distribution of the disturbance of the model is then assumed to be $\varepsilon_t | \psi_{t-1} \sim N[0,\sigma^2_t]$ where $\varepsilon_{t-1}=\psi_{t-1}$ or all information through time t-1. The conditional variance is defined as

$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \alpha_2 \varepsilon^2_{t-2} + ...\alpha_q \varepsilon^2_{t-q} + \delta_1 \sigma^2_{t-1} + \delta_2 \sigma^2_{t-2} + ...\delta_p \sigma^2_{t-p}$

For the case of GARCH(1,1), this equation is $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon^2_{t-1} + \delta_1 \sigma_{t-1}^2$. The power of the GARCH specification is that a GARCH(1,1), with a small number of terms, p=1,q=1, can perform as well or better than an ARCH model with many, as in an ARCH(8) specification with q=8. The lag distribution of the GARCH(1,1) is flatter than that of the ARCH(8) specification that leads to a better fit of the data than the ARCH (8) specification.

The regression includes estimates of α_0, α_i and δ_t denoted ARCH0, ARCH1 and GARCH1. A nonnegativity constraint is imposed of p> 0, q > 0, $\alpha_0 > 0$, $\alpha_i \geq 0$,$\delta_t \geq 0$ so as to avoid negative parameter estimates. The exponential form of GARCH, denoted EGARCH, relaxes the nonnegativity constraints of the linear GARCH model. The conditional variance σ_t^2 is an asymmetric function

of lagged disturbances ε_{t-1}:

$$\ln(\sigma_t^2) = \alpha_0 + \sum_{i=1}^{q} \alpha_i g(z_{t-i}) + \sum_{j=1}^{p} \delta_i \ln(\sigma_{t-j}^2)$$

where $g(z_t) = \theta z_t + \delta_i\ [|z_t| - E|z_t|\ ]$

and

$$z_t = \frac{\varepsilon_t}{\sqrt{\sigma_t^2}}$$

If δ_i , the GARCH variable, is greater than 0, the model predicts a deviation of $|z_t|$ from its expected value that causes the variance of ε_{t-1} to be larger than otherwise. The θ parameter allows this deviation to be asymmetric. It measures the degree to which an innovation affects volatility. If $-1 < \theta < 0$, for example, a positive innovation increases volatility less than a negative innovation. If $\theta < -1$, a positive innovation actually reduces volatility while a negative innovation increases it.

As in the case of ARCH models, OLS is still the best linear unbiased estimator but the nonlinear GLS (Generalized Least Squares) estimator is more efficient. To estimate the nonlinear GLS, therefore, the maximum likelihood method is used with the GLS model. The estimates obtained at convergence are linear, but the method used to obtain them is not a linear regression. As explained in Chapter 2, the Berndt, Hall, Hall and Hausman (1974) algorithm is used for iteration.

For normally distributed disturbances, the log likelihood for a sample of T observations is

$$lnL = \sum_{t=1}^{T} -\frac{1}{2} \quad [\ln(2\pi) + \ln\sigma^2_t + \varepsilon^2_t \sigma^{-2}_t] \text{ where } \varepsilon_t = y_t - \beta' x_t$$

This is just a special case of the familiar log-likelihood function for a normal distribution of T observations:

$$lnL = -\frac{T}{2} \quad [\ln(2\pi) + \ln\sigma^2 + \varepsilon_t^2\sigma_t^{-2}] \text{ where } \varepsilon_t = y_t - \beta' x_t$$

Ln L = ln $f_t(\theta) = l_t(\theta)$ and $\theta = (\beta', \gamma')'$. The vector γ is equal to (α, δ). It is the vector of the error and memory terms. The following equations are the first- and second-order conditions used for the iteration. All variables except γ (a vector) have a subscript t. Derivatives of lnL are obtained by summation.

1)

$$\frac{\delta l}{\delta\gamma} = -\frac{1}{2}\left[\frac{1}{\sigma^2} - \frac{\varepsilon}{(\sigma^2)^2}\right]\frac{\delta\sigma^2}{\delta\gamma} = \frac{1}{2}\left(\frac{1}{\sigma^2}\right)gv$$

$$where\ g = \frac{\delta\sigma^2}{\delta\gamma}\ and\ v = \frac{\varepsilon}{\sigma^2} - 1$$

2)

$$\frac{\delta^2 l}{\delta\gamma\delta\gamma`} = \frac{1}{2}v\frac{\{\delta(\frac{1}{\sigma^2})g\}}{\delta\gamma`} - \frac{1}{2}\left(\frac{g}{\sigma^2}\right)\left(\frac{g}{\sigma^2}\right)`\frac{\varepsilon^2}{\sigma^2}$$

$\gamma^{i+1} = \gamma^i - H^{-1}g$ is the algorithm for estimating the variance parameters that uses Newton's method of trust region. H indicates the Hessian of γ and g indicates the first derivative vector of lnL, (l), with respect to γ. The starting values are taken from the classical linear regression. At convergence, a normality test is imposed to determine whether the residuals of the GARCH model are normally distributed. The null hypothesis H_0 is that they are normally distributed and the alternative hypothesis H_a is that they are not. If the normality test yields results that are statistically significant, the null hypothesis that residuals are normally distributed is rejected. This rejection is designed to detect misspecification of the model such as omitted variables.

The misspecification, as Engle (1982) describes it, could be due to structural change or omitted variables. While the ideal situation would be to correct the specification, the ARCH-like model offers a model that would fit the error term. It seems an easier fit to data whose error terms do not conform with the assumption that they are normally distributed. The GARCH specification is an alternative to the misspecification and is consistent with an attempt to fit a model to the data despite omitted variables.

Conclusion

The underlying purpose of this study is to explain the way in which the stock price volatility has been computed. It puts the estimation in the context of the econometric and financial literature. This chapter describes how the GARCH specification is being used on a new set of data. The EGARCH(1,1) specification is being used to estimate the volatility in recognition of the clustering of the residuals of stock price data and because it is consistent with the learning process of rational expectations. The point is to attempt to explain a change in stock price volatility with country-specific measures of the determinants of that volatility.

Chapter 4

Model and Justification of Chosen Variables

Introduction

This section presents the model's assumptions and serves to justify the explanatory variables chosen to explain the percentage change of standard deviation computed using the Exponential GARCH(1,1) form. It explains why each variable is relevant to explaining changes in stock price volatility. All explanations should be taken in the context of the assumptions of the model. The driving force behind this model is confidence. It is the change in confidence that leads to a change in stock price and stock price volatility.

Assumptions of the Model

The first assumption of the model is that no arbitrage opportunities are possible. Investors have already capitalized on any opportunities to obtain a higher stock return in one market over another. The price being observed in this model is the settled price once traders have profited from such opportunities.

Having assigned a no arbitrage condition, the second assumption is that all investors have the same preferences and expectations. This simplifies the analysis by not worrying about agents with one set of preferences versus those with another. Similarly, we don't have to worry about agents with one set of expectations versus those with another. Any treatment of investment risk requires knowledge of investor preferences with regard to risk. Bearing in mind the portfolio selection problem of handling risk and return, preferences are made homogeneous so that there is no confusion as to whether there is any endogeneity between the change in volatility and the right-hand variables.

The third assumption is that country markets are complete to account for all possible states. All possible states of nature are insurable but their probabilities are unknown. No short sales are allowed ensuring positivity of returns and hence prices. Taxes and transaction costs are assumed to be zero so that stock price volatility could not possibly reflect them.

The fourth assumption is that the market is initially in equilibrium where data residuals are assumed to be homoscedastic. This is the null hypothesis of the heteroscedasticity test using the GARCH(p,q) specification. A rejection of this null hypothesis would suggest the presence of heteroscedasticity and higher-order autocorrelation. This fourth assumption allows deviation from this standard of homoscedasticity to be examined as a phenomenon without trying to model all possible market states.

The fifth assumption is that capital mobility is assumed to be highly elastic. The higher the interest rate, the greater is the capital inflow. The domestic and foreign interest rates are not equal.

The Hypotheses of the Model

There are two hypotheses of this model. The first is that for individual countries, the ln (stock price volatility) can be explained by the ln (short-term interest rate), ln (U.S. Treasury bill short-term rate), ln (exchange rate), the percent change in the current account, the percent change in deficit/surplus, ln(exports), the percent change in consumer prices and the squared term of the inflation rate.

The first hypothesis of the study is represented by the following log-linear type regression:

$$y=\beta_0+ \beta_1 x_1 + \beta_2 x_2+ \beta_3 x_3+ \beta_4 x_4 +\beta_5 x_5 +\beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \varepsilon_t$$

where

y = logarithm of standard deviation of stock price
x_1= logarithm of short-term interest rate
x_2= logarithm of the U.S. Treasury bill (3-month) rate
x_3= logarithm of exchange rate

x_4=% change in current account
x_5=% change in deficit/surplus
x_6= logarithm of exports
x_7=% change in consumer prices, or inflation
x_8= inflation^2

A Yule-Walker model is specified on all twenty-three countries. This model differences out the autocorrelation. The Yule-Walker method estimates β using GLS with the estimation of the coefficient of autocorrelation φ using the Yule-Walker equations applied to the sample autocorrelation function. The Yule-Walker method starts by forming the OLS estimates of β. Recall that the Yule-Walker equations are:

$$\varphi_j = \phi_1\varphi_{j-1} + \phi_2\varphi_{j-2} + \ldots\phi_p\varphi_{j-p} \qquad \text{for all } j= 1,2 \ldots\ldots$$

A regression model with autocorrelated disturbances is described in the following fashion:

$$y_t = x_t'\beta + v_t$$

$$v_t = \varepsilon_t - \quad v_{t-1} \qquad \ldots v_{t-m}$$

$\varepsilon_t \sim N(0,\sigma^2)$. Let $\varphi = (\varphi_1, \varphi_2, \ldots \varphi_m)'$ the vector of autoregressive parameters computed from the Yule-Walker equations and let the variance matrix of the error vector $v = (v_1, \ldots , v_N)$ be Σ.

$$E(vv') = \Sigma = \sigma^2 V$$

If the vector of autoregressive parameters, φ, is known, the matrix V can be computed from the autoregressive parameters. Given the existence of a matrix V, efficient estimates of the regression parameters β can be computed using Generalized Least Squares (GLS). The GLS method yields unbiased estimates of the variance σ^2.

A comparison of the results from these countries begs the question of how a change in stock price volatility in one country affects another. It is one thing to observe the country's results in isolation. It is another to observe how a change in one country might affect the others. The recognized globalization and interdependence of country markets warrants some examination of this question.

The second hypothesis is that the twenty-three individual country markets are interdependent and directly influenced by the U.S. market. A system of equations is drawn up from the country stock price data. The aim of estimating a system of equations is to examine the nature of that interdependency. A Vector Autoregressive specification, (VAR), has been chosen for estimation because autocorrelation is present in time series data. The system of equations looks like this:

$$y_{it}=a_1 y_{it-1}+a_2x_{it-1} + \varepsilon_t$$

....

$$y_{nt}=a_1 y_{nt-1}+a_2 x_{nt-1} + v_t$$

where y_{it} is the country being modelled as the dependent variable and x_{it} represents the countries that serve as independent variables. The dependent variable is a function of its lagged values as well as a function of lagged values of the independent variables (for periods t and t-1). As each country is modelled as the dependent variable, the countries which serve as independent variables change. Both the y_{it} and the x_{it} variables change throughout the system of equations.

The VAR system tests for Granger causality, i.e. whether the independent variable can help forecast the dependent variable and vice versa. Using GLS estimation, the restricted regression is H_0: β_i's = 0. If the null hypothesis is rejected, there is evidence of a relationship between the independent variables (the "x " variables) and the dependent variable, i.e. Granger causality. F-tests are presented that test the null hypothesis. Given the presence of lagged values of the "y" variable on the right-hand side of the equation, the GLS estimation produces more efficient estimates than OLS.

Data

The variables chosen as macroeconomic indicators reflect the relative stability of the country's domestic economy as well as its balance of trade with respect to other countries. A common variable name is given rather than a specific name because the measure may differ across countries, e.g. the lending rate may measure the interest rate in one country versus the commercial lending rate in another.

The study uses weekly data from 1989 to 1994 and in some cases to 1995. Data for variables are collected in dollar terms to put all data in a common currency. This way results are directly comparable across countries.

Explanatory Variables

The log of stock price volatility is presumed to be correlated with the explanatory variables. For these variables, percentage changes are only taken when log values could not be computed because of negative values in the observations. The change in the current account and deficit/surplus are similarly measured in percentage changes. They could not be measured in logs because they have negative values in their observations. .

A change in stock price volatility can result from increased investment if the stock price rises faster than that change can be predicted. That possibility, however, is assumed to be smaller than the effect of increased confidence dampening the change in stock price volatility. It is assumed that the increase in the interest rate will attract foreigners to "lend" (i.e. invest) in the country's asset market where assets will earn a high return as the interest rate rises. This increased investment will bolster confidence in the stock price level. The capital inflow will cause the stock price to be more predictable [7]. The increased confidence in the stock price level will reduce the change in stock price volatility. The increased investment will lead to greater confidence in the investment environment, so that an unanticipated increase in the interest rate will result in a smaller change in stock price volatility since confidence has increased.

In choosing the interest rate, an effort has been made to choose one that reflects conditions in the private sector to the greatest extent possible. A commercial interest rate, for example, better reflects market conditions than a discount interest rate as it fluctuates more than a discount interest rate subject

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[7] Michael Raney, "Common Factors Affecting Stock Price Volatility," (Ph.D. dissertation, University of Northern Colorado, 1986), 25.

to government intervention. Furthermore, it reflects some aspect of privatization and market openness in countries that have recently liberalized their markets in attracting foreign capital, such as Argentina, Greece, or Pakistan. A commercial nominal interest rate in an open market will attract more foreign capital than it will in a relatively closed market. Since it is less subject to government intervention, the commercial rate reflects how well it can attract foreign capital into the country with the attraction of a high return from investment. The nominal interest rate in this model is allowed to change to reflect the attractiveness of the country's investment environment.

The log of the U.S. Treasury bill short-term rate reflects the extent to which movements in the United States stock market affect these emerging markets. Since the United States has been considered a dominant market in the world market, including a U.S. interest rate reflects its influence on these emerging markets. An interest rate is linked with the national debt, domestic credibility and hence stock price volatility. As the Treasury bill short-term rate is an interest rate backed by the government, it is considered a relatively risk-free rate. It reflects the effect of the fluctuation of one of the most secure U.S. interest rates on these emerging markets. A U.S. interest rate that fluctuates more may reflect the effect of a particular event that caused that movement, but the inclusion of a risk-free rate reflects a more typical effect of the United States on these markets.

The log of the exchange rate reflects the strength of the country's trading power. If the official exchange rate rises in dollar terms confidence in it increases either from reduced public debt, increased capital inflow, or government revenue. A reduction in public debt or an increased capital inflow has made international investors more confident in the local currency. The exchange rate captures international credibility regarding balance of payments and public spending as well as from net exports.

The percentage change in current account is taken to reflect another aspect of international credibility, the rate at which the country accumulates foreign assets. The current account is the change in the net foreign asset position. The percentage change in current account reflects whether the country is accumulating net foreign assets slower than it had been earlier. If this is the case, a slow accumulation of foreign assets can eventually mean that the country's international credibility will drop as it becomes a poorer country.

In this model a change in the current account could cause a shift in the demand curve for the country stock since it represents an exogenous change in demand. A current account surplus would suggest a favorable trading position that would shift the country stock's demand curve to the right, causing its stock price to rise along an upward sloping supply curve.

Conversely, volatility in stock prices would grow as the current account surplus decreased. The higher the current account deficit, the more stock price would fluctuate as a result of loss of confidence. The loss in confidence would translate into a loss in predictability in stock price. This would in turn lead to an increase in stock price volatility.

The percentage change in the country's government deficit/surplus, i.e. without interest payments included, reflects the government's credibility in the way that the current account reflects the country's international credibility. In human capital theory, for example, the individual is willing to "overspend" on education in the short run in order to increase spending power in the long-run. This short-term overspending is viewed as an investment. To the extent that this reasoning is analogous to government deficit spending, how public confidence is affected by deficit spending depends on the perception of this change in spending. If the change is viewed as an investment, it can increase confidence. If it is viewed as an indulgence, however, it could dampen confidence. A large budget deficit reflects badly on the country's domestic investment environment because it could lead to crowding out in the private sector. The budget deficit could take resources away from investing in the country to finance overspending from a previous time period. In that case, the coefficient's expected sign would be positive. Since the change in deficit/surplus can change public confidence one way or the other, it is worth including as an explanatory variable. Like the current account variable, if it is not included, it is not recorded for a given country on a usable basis.

The log of exports reflects the country's level of in ternational trade by reflecting its international competitiveness. Unlike the log of exchange rate or percentage change in current account, it captures only the effect of a change in demand for exports. The log of exchange rate reflects changes in both the domestic and external economy. The log of exports reflects changes in the external economy primarily. Logically, this has the effect of increasing the current account, leading to a reduction in stock price volatility if that change is positive.

The percentage change in consumer prices is included because the stock price volatility has been associated with hyperinflation.[8] The squared

[8] Raney, 1.

inflation term is included to capture a degree of hyperinflation that has been identified in many of these countries. It measures the rate at which inflation is increasing.

Chapter 5

Estimation and Results

Data

This study uses weekly data of stock prices found in The Financial Times and the Emerging Stock Markets Fact book issued by the International Finance Corporation. It uses monthly, country international and macroeconomic variables found in the International Financial Statistics. Any difference in initial base date for the level of stock price indices is therefore less important.

This data are also marked by missing values for 1993. Since the number of missing values is not great, the data have been left in this form because it is believed that the presence of missing values is relevant to stock price volatility. The missing values are associated with the low volume of the recorded trading.[9]

[9] Glenda Wenchi Wong, "The Effect of Stock Exchange Listing on Trading Volume, Market Liquidity, and Stock Price Volatility,"(Ph.D. dissertation, University of Illinois at Urbana, 1984),2.

Graphs

The first set of graphs is of country stock prices. A record of the country stock prices gives the reader a good sense of the direction the stock price volatility might take. There are some patterns in the stock prices that become apparent. The distributions of price indices of China, Hungary, Poland, and South Korea (hereafter Korea) are generally downward sloping. Argentina, Brazil, Chile, Colombia, Greece, India, Indonesia, Jordan, Malaysia, Mexico, Pakistan, Peru, the Philippines, and Venezuela are more upward sloping. Portugal, Sri Lanka Turkey, Thailand, and Zimbabwe are not particularly upward- or downward-sloping.

The second set is of country stock price volatility and whether it follows a leptokurtic distribution with heavy tails. The EGARCH(1,1) model has been used to compute the conditional variance [10]. The standard deviation of that conditional variance is used to estimate the stock price volatility.

Overall Explanatory Power of the Model

The Yule-Walker estimation is used for the individual country

[10] except Turkey, for which the conditional variance could not be estimated using the EGARCH(1,1) model.

estimation. As described in Chapter 4, it corrects for the autocorrelation in the time series data by estimating a coefficient of autocorrelation φ. The autocorrelation corrected estimates are computed by GLS. The R^2 term is provided as a general form of explanatory power of the model. The R^2's from the Yule-Walker regression are taken since they account for the autocorrelation in the data. The R^2 is the measure of how well the next value can be predicted using the structural part of the model and the past values of the residual. The structural part of the model is the explanatory part of the model. The use of the residual addresses the autocorrelation in the data. There is a wide range in overall explanatory power of the model across these countries. The lowest is Korea at .08 and the highest is Zimbabwe at .97. There are seven countries with R^2's between .08 and .37. Fourteen countries have R^2 's between .75 and .97. For two countries, Turkey and Venezuela, the Yule-Walker model could not be fit.

Results

In Table 1, the explanatory variables of the model show some statistical significance across countries. Many of the estimates are coefficients below 1 toward achieving the finite variance that is required for an equilibrium. The intercept term shows statistical significance in only five out of the 21 countries where the model could be fit, indicating that the explanatory power of that variable is not overwhelmingly more than that of the others.

The log of interest rate shows statistical significance (at the 5- or 1-percent level) in Colombia, Greece, Hungary, Korea and Mexico. It is significant at the 6 percent level for India. Of these countries, Hungary and Mexico have had the most publicized capital movement during the 1989-1995 period; Hungary, because of its increased privatization as an emerging market, and Mexico, because of the peso crisis of December 1994.

The log of U.S. Treasury bill rate shows statistical significance for Argentina, China, Colombia, Greece, Indonesia, Mexico, Poland, and Zimbabwe. While this evidence of a U.S. effect is consistent with expectations, it is surprising that the U.S. effect is not present for more of these countries. For countries such as Colombia or Mexico, a large U.S. influence is not surprising. But if Poland shows evidence of such a U.S. influence, it is odd that Hungary would not show such an influence. They both are in the same region and have a similar relationship to the United States. The difference in results could be due to the differences in their relationship to the U.S. stock market. Similarly, if Indonesia shows such an influence, it is surprising that neither Pakistan nor India shows this influence. If anything, countries such as India and Pakistan are tied militarily to the United States more than is Indonesia.

The log of exchange rate shows a statistically significant correlation in Greece, Malaysia, and Mexico. The significance for Mexico's coefficient can be explained by the devaluation of the peso in December 1994, particularly since it implies a rise in stock price volatility. The significance of the coefficients for Greece and Malaysia could reflect the effect of scandals in their respective stock markets that affected the confidence in each of their currencies. [11]

The coefficient of percentage change in current account does not show statistical significance at the conventional level in any of the 21 countries tested. Brazil's and China 's coefficients are only significant at the 9 and 7 percent levels respectively. For Peru, the coefficient of deficit/surplus variables shows statistical significance only when the percentage change in current account is not included. Its negative sign indicates that a drop in debt

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[11] Mark Mobius, The Investor's Guide to Emerging Markets. (London: Pitman Publishing Longman, U.K., Ltd.), 133.

fluctuation can be correlated with decreasing change in stock price volatility.

For China, Malaysia, Pakistan and the Philippines, the coefficient of log of exports shows statistical significance. In Chile and Hungary the coefficient is significant at the 7 percent level. Considering that the log of exchange rate coefficient for Malaysia is also significant, the two significant coefficients could indicate export-oriented growth for that country. However, in all countries the coefficient of log of exports is positive. This casts doubt on the argument that an increase in net exports, by adding to the current account, should reduce stock price volatility. It suggests that for the countries listed above, export-oriented growth has lead to stock price instability in the short term.

Argentina, China, the Philippines, and Poland show a statistically significant coefficient of percent change in consumer prices and stock price volatility. Colombia's, Jordan 's and Zimbabwe's coefficients show significance at the 6, 6 and 7 percent levels respectively. The coefficient of hyperinflation variable shows statistical significance for Argentina, the Philippines, Poland, and Zimbabwe. Colombia and Peru 's coefficients show significance at the 8 and 6.5 percent levels respectively. This suggests that inflation is increasing at a decreasing rate, or that the country is gaining control of its hyperinflation.

Results of VAR section

Table 2 are for the results of the VAR section. The results are the F-tests for the positive percentage change of stock price volatilities. In the F-tests the null hypothesis is that the coefficient β's are zero. If the null hypothesis is rejected, it is because the data suggest Granger causality between the respective markets of statistical significance at the 5- or 1-percent level.

The countries logistically could not be run all together. They were grouped together by time period and with the United States included in each group.[12] The first set of results is for ten Latin American and European and Asia countries respectively. There is a statistical relationship between Argentina, Chile and Venezuela; Brazil and Korea; Chile and Venezuela; Mexico and Venezuela; Venezuela and Brazil, Mexico, the Philippines and Portugal; and the United States, Jordan, and Malaysia.

The second group is between the Colombia, Greece, Thailand and the United States. Thailand and Greece are the only countries that show a

[12] Hard disk memory limitations precluded running more than 14 countries together.

statistically significant relationship, although the United States and Greece show a relationship at the 8 percent level. The third group is Indonesia, India, Pakistan and the United States. India and Indonesia show a significant relationship and Indonesia and Pakistan show a relationship at the 5.5 percent level. The data do not show a relationship of statistical significance between these countries and the United States.

The fourth group is for China, Hungary, Peru, Poland, Sri Lanka, the United States and Zimbabwe. There are relationships of statistical significance between China, Hungary and Zimbabwe; and the United States, Hungary and Peru.

The countries in given regions, such as in Latin America, seem more interdependent than with the United States as a whole. Regarding the United States, few countries rejected the null hypothesis of Granger causality for a change in stock price volatility. There seems to be more of an effect amongst each other than with the United States.

While a number of these markets show that they are influenced by United States, this data do not show that the United States dominates these markets. The results of the test of the first hypothesis demonstrate that the U.S. Treasury bill rate had significant explanatory power for a number of the

21 countries estimated. The results of the test of the second hypothesis, however, are mixed. There is evidence supporting the alternative hypothesis of interdependence in stock price volatility between these markets and there is evidence supporting the null hypothesis that the change in U.S. stock price volatility does not affect that of these markets.

Chapter 6

Conclusion

The EGARCH(1,1) model has been applied here to emerging markets for the first time. The econometric methods described in Engle (1982) and Bollerslev (1986) have been used to model stock price volatility as the conditional variance of stock price indices. The conditional variance is computed using the EGARCH(1,1) econometric method and the standard deviation of that variance is used to estimate stock price volatility. The stock price volatility has been taken as a dependent variable in a Yule-Walker regression that differences out the autocorrelation.

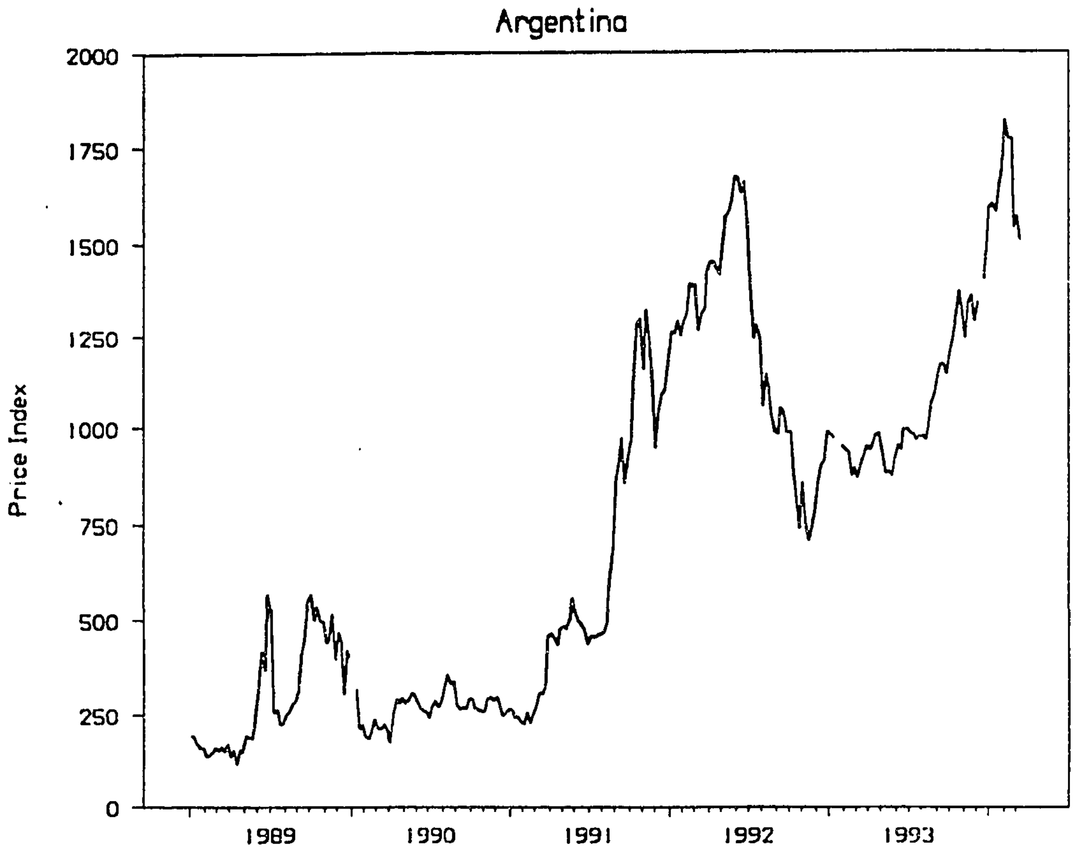
The first hypothesis is that the log of stock price volatility could be explained by domestic macro and balance of payment variables. Across twenty-three emerging markets, the following variables were selected to explain log of stock price volatility: the log of nominal interest rate, the log of the U.S. Treasury bill short-term rate, the log of exchange rate, the percentage change in deficit/surplus, the percentage change in current account, the percentage change in consumer prices and the squared inflation rate. The variables that have shown statistical significance across the 21 countries for which the model could be fit are the log of interest rate, the log of the U.S.

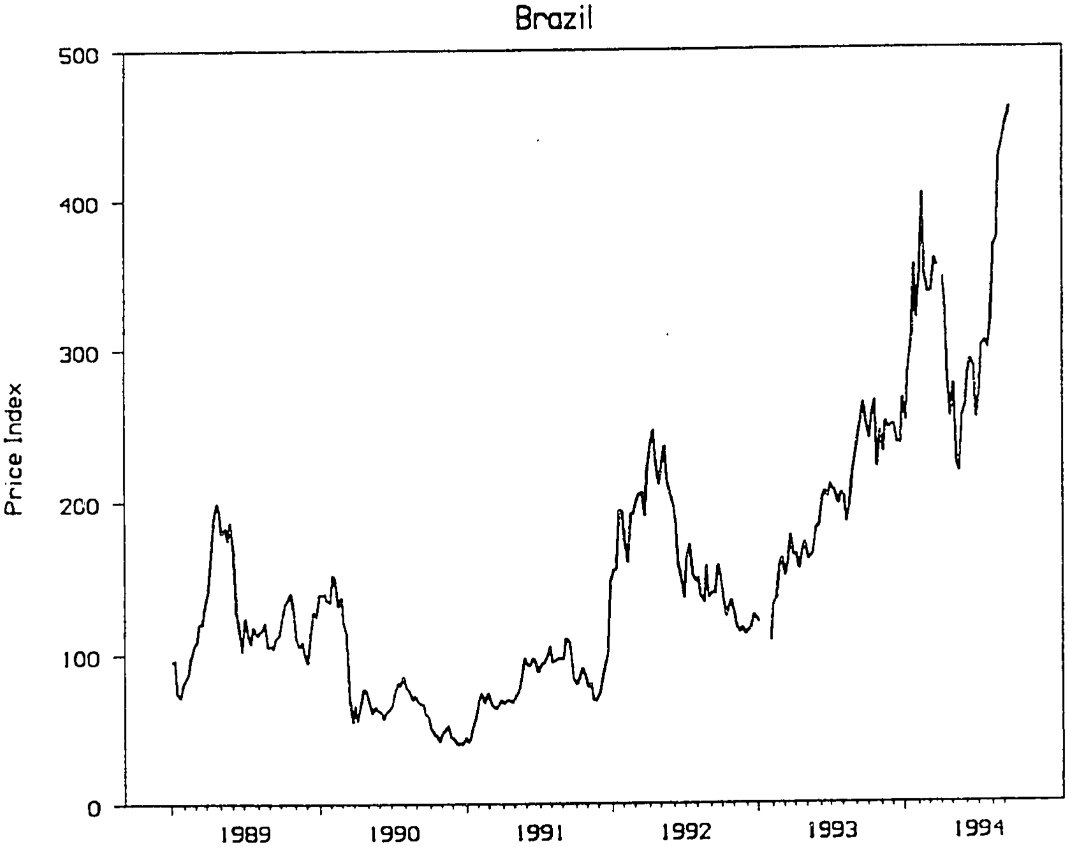
Treasury bill rate, the log of exchange rate, the inflation rate and the squared inflation rate. The overall explanatory power of the model ranged from .08 for Korea to .97 for Zimbabwe. Fourteen countries of the 23 countries had R^2 's between .75 and .97.

The second hypothesis is that the twenty-three emerging markets are interdependent and directly affected by the U.S. market. The disturbances are tested for correlation. An F-test is run between countries which tests whether the β's, the coefficients of each equation of the system, are zero. That is the null hypothesis. If the null hypothesis is rejected, it suggests the presence of Granger causality. This restates whether the disturbance terms ε_t are correlated. There was evidence of a relationship between these emerging markets and the United States, but not many of the countries tested were directly affected by the U.S. market. The Latin American countries were the most closely affected by the United States and then countries such as Korea in the other regions of Europe and Asia. The logs of stock price volatility tended to be the most closely linked in Latin America and then Asia. The European countries tended to be the least interrelated.

In conclusion, this study explains the percentage change in stock price volatility over time with macro and balance of payment variables. For the first hypothesis, the right-hand variables do show some explanatory power across countries and the overall explanatory power of the model is reasonably high. For the second hypothesis, there is evidence of interdependence between changes in stock price volatility of these emerging markets but little evidence that the U.S. directly affects them.

1. Stock Prices

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1993
1994


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1992
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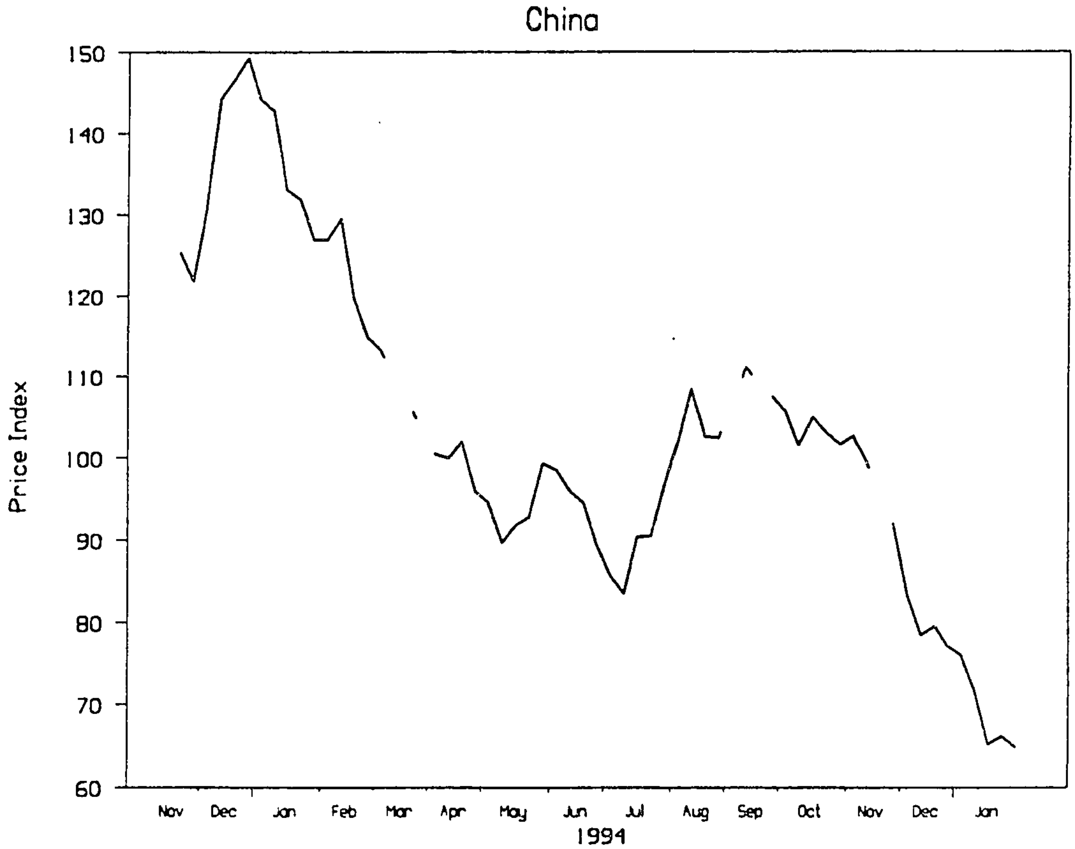
China
Price Index
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140
130
120
110
100
90
80
70
60
Nov
Dec
Jan
Feb
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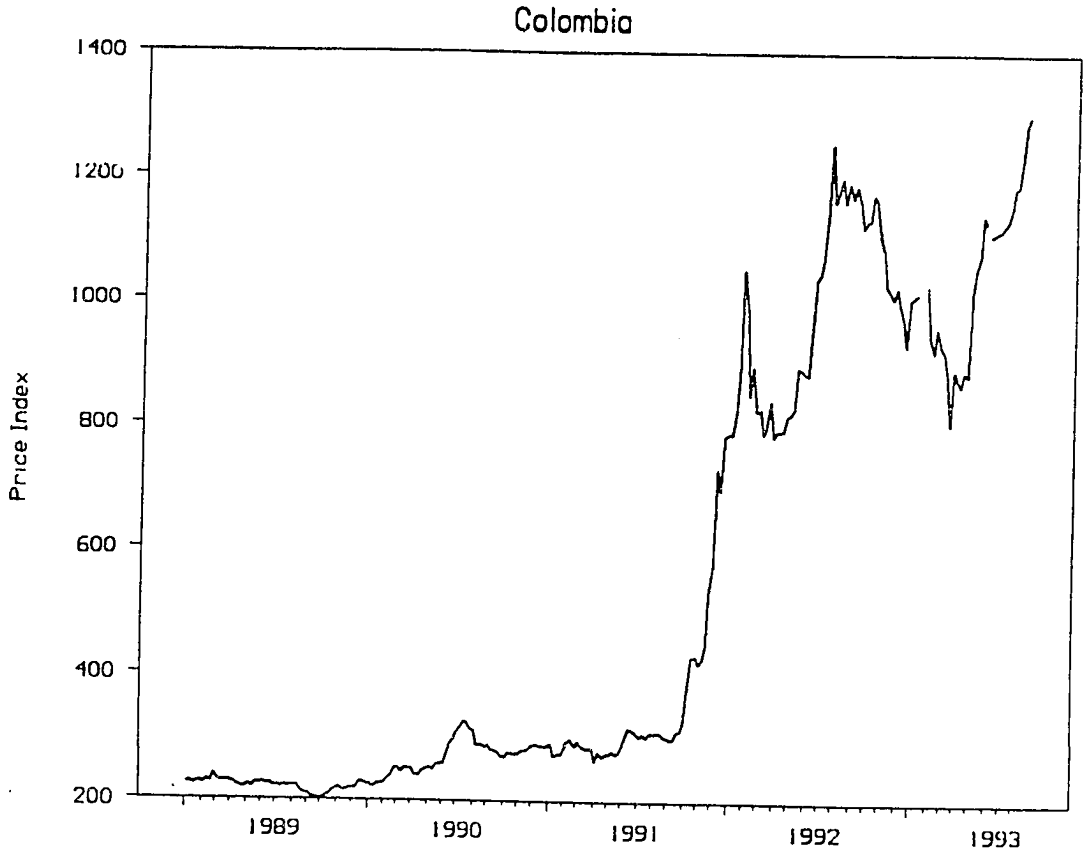
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
1994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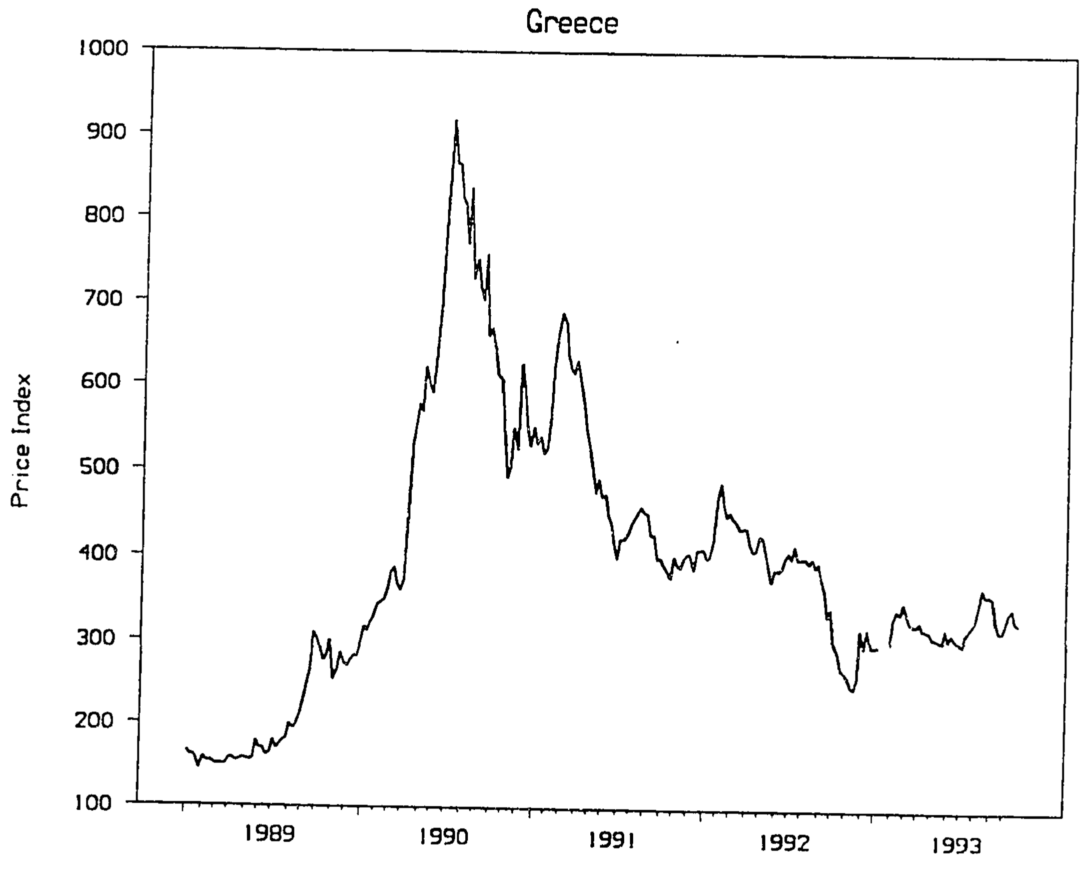
1200
1000
800
600
400
200
Price Index
1989
1990
1991
1992
1993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900
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500
400
300
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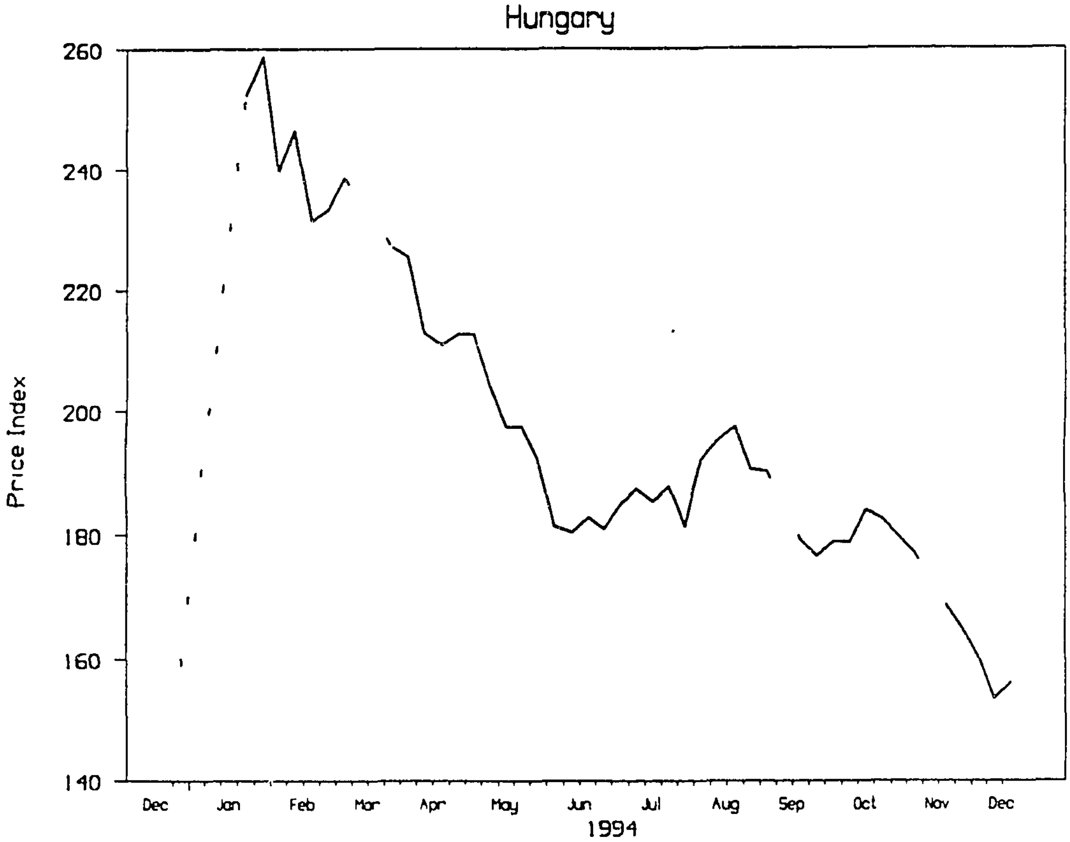
1991
1992
1993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Price Index
260
240
220
200
180
160
140
Dec
Jan
Feb
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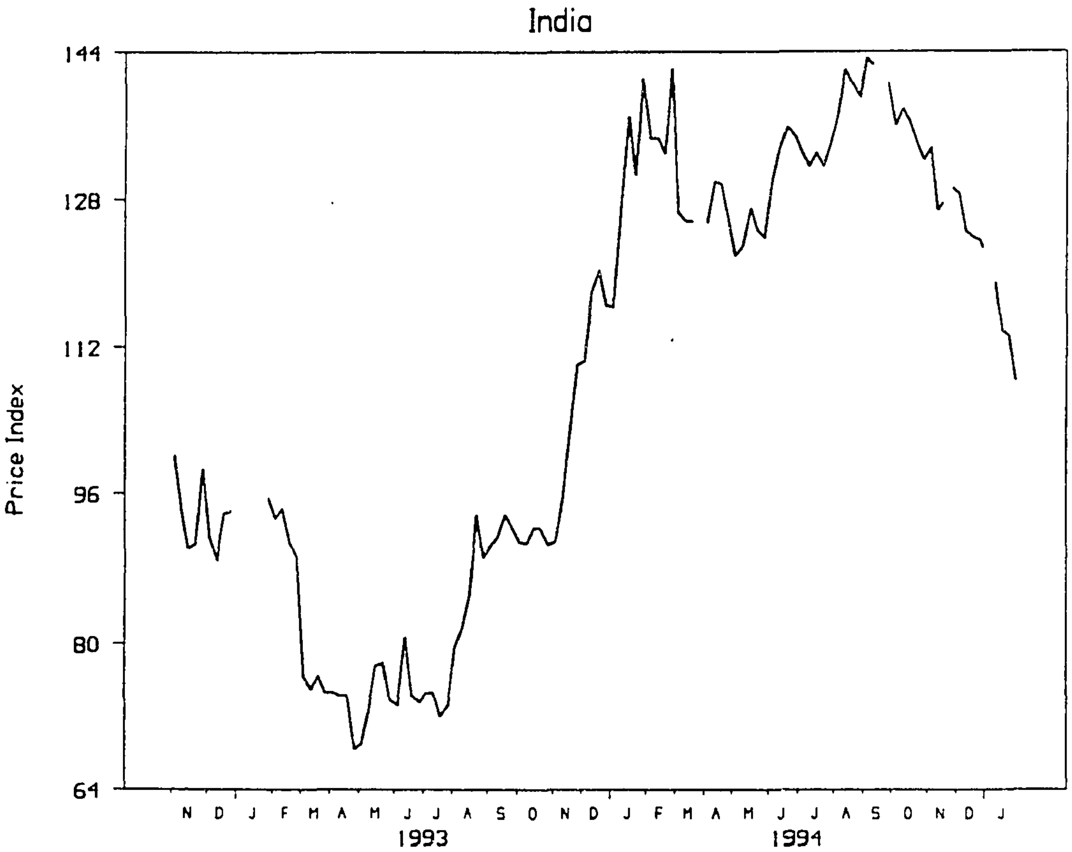
Oct
Nov
Dec
1994


India
Price Index
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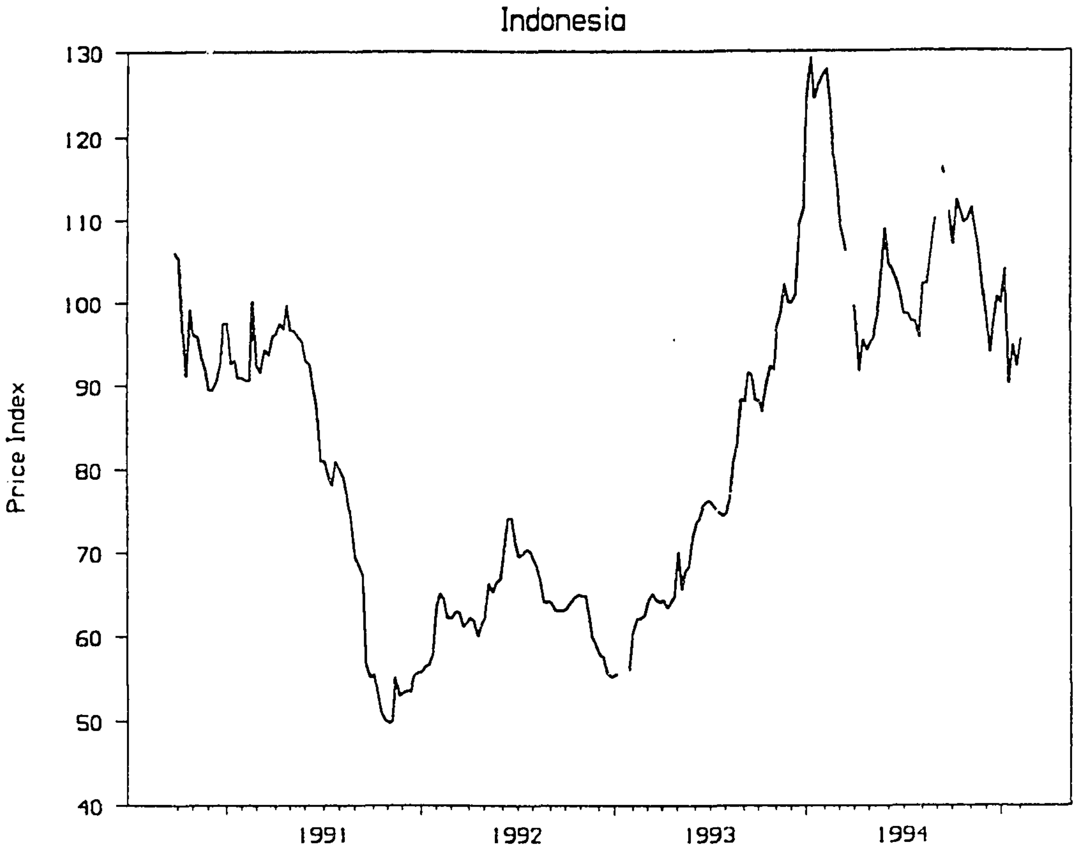
128
112
96
80
64
N D J F M A M J J A S O N D J F M A M J J A S O N D J
1993
1994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60
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1993
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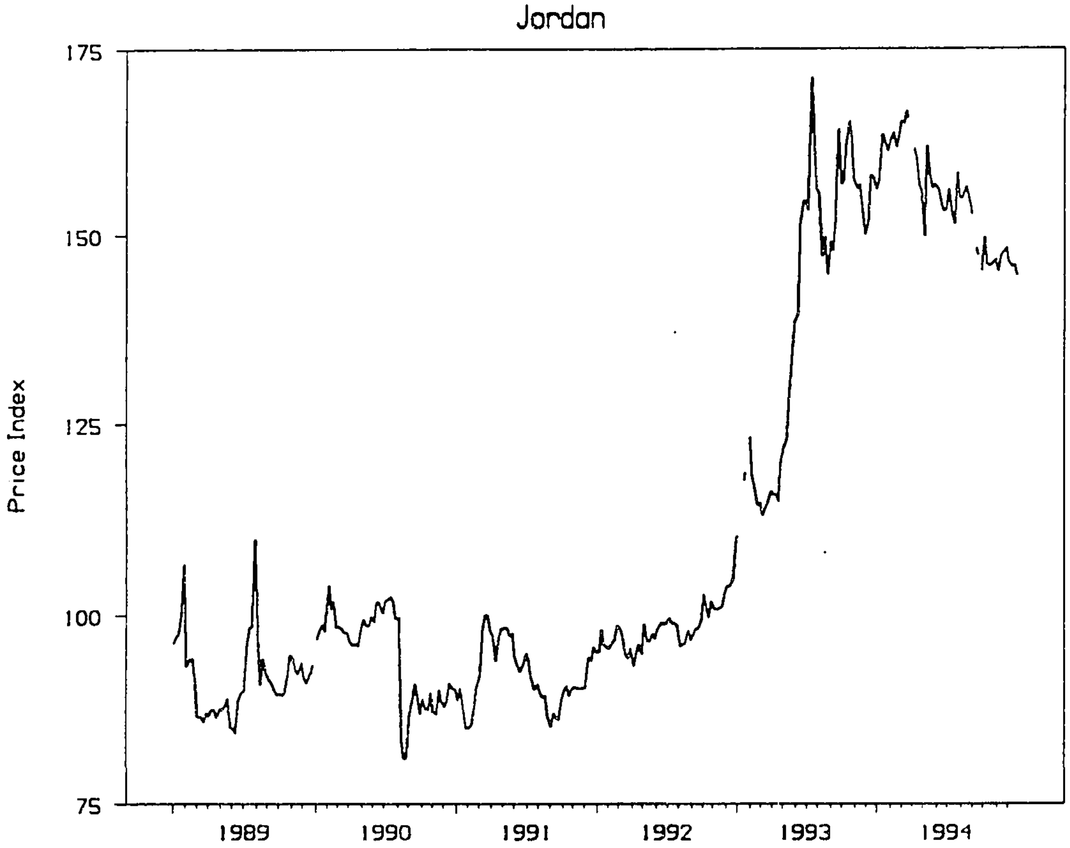
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125
100
75
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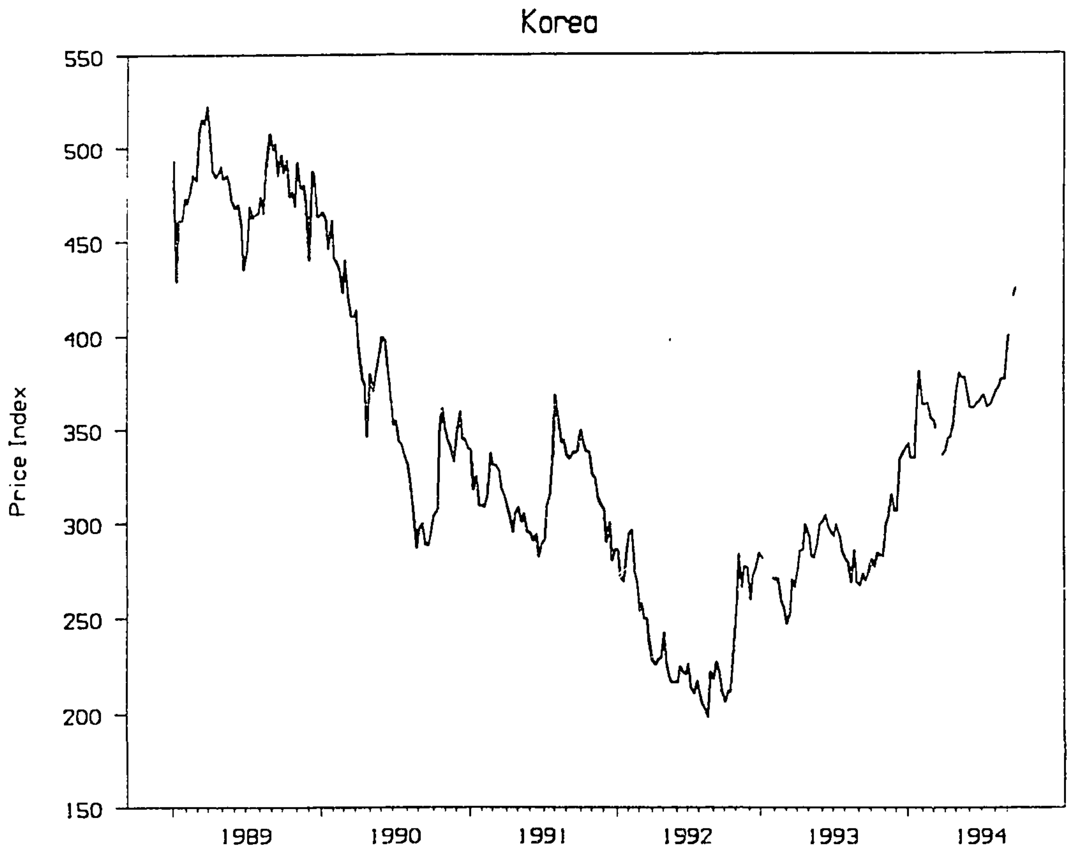
1989
1990
1991
1992
1993
1994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Price Index
550
500
450
400
350
300
250
200
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1989
1990
1991
1992
1993
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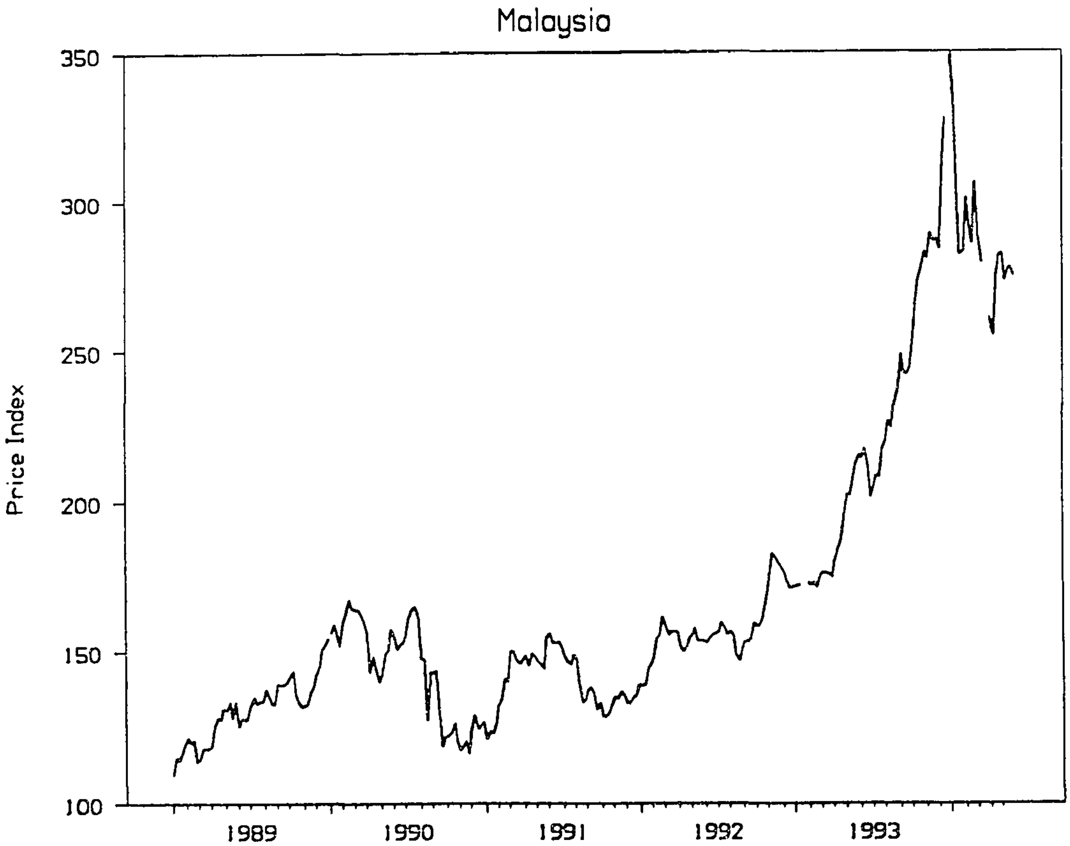
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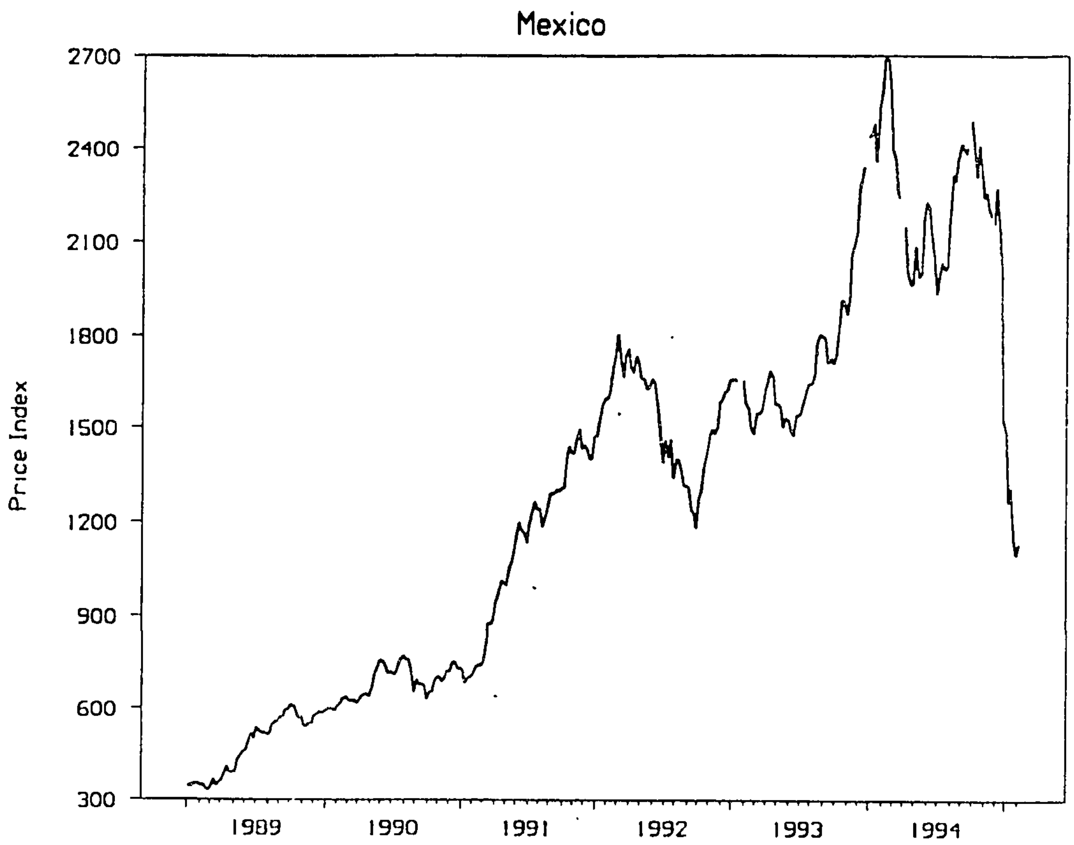
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600
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1989
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1991
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1993
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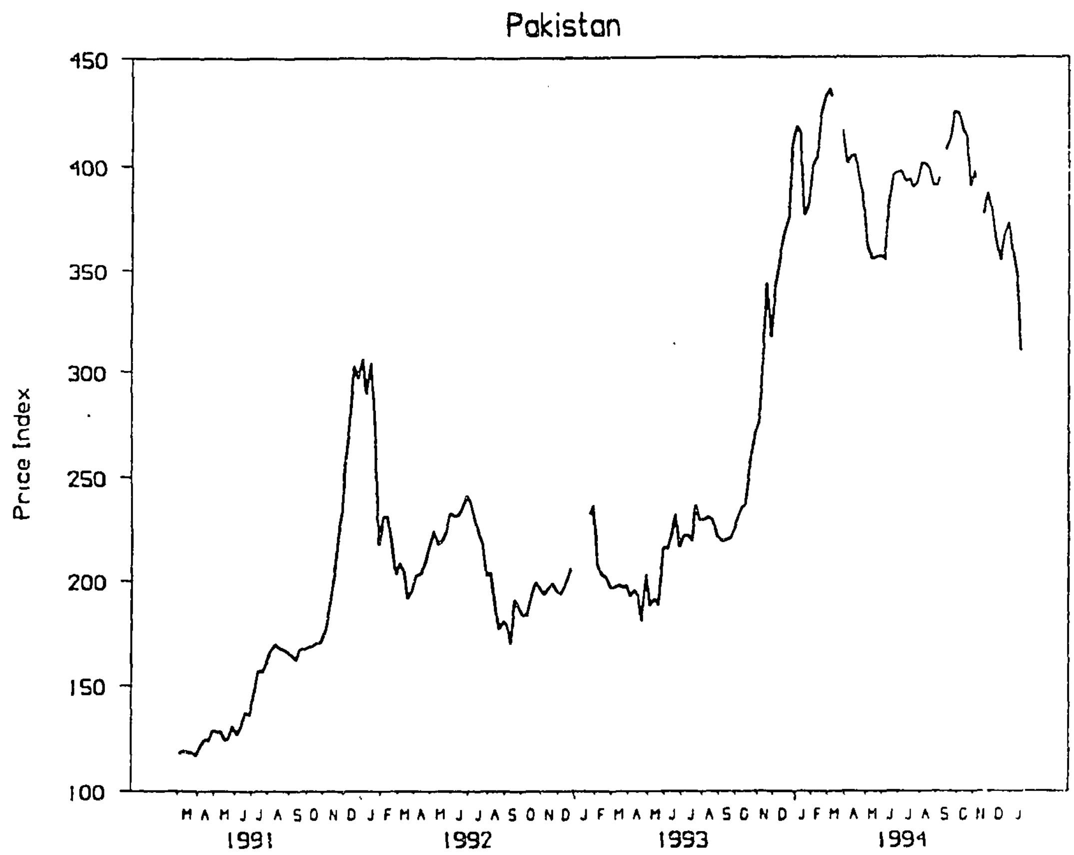
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100
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1991
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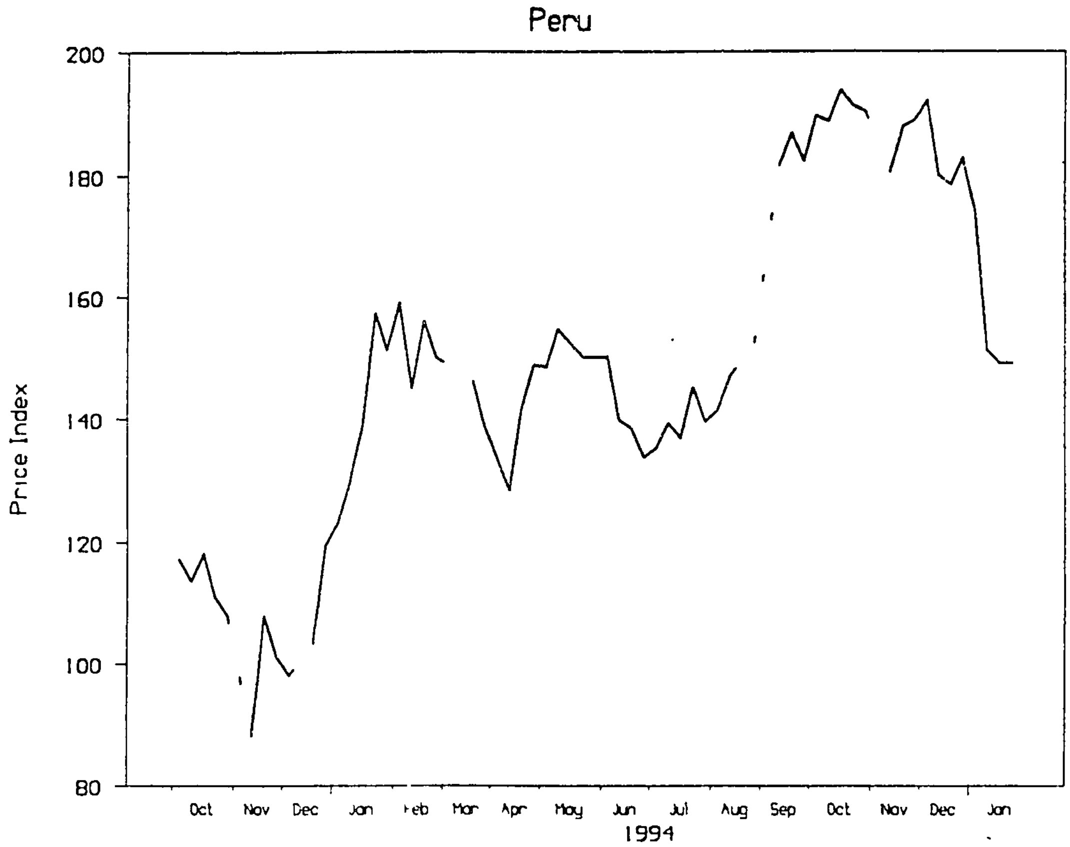
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180
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Price Index
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Nov
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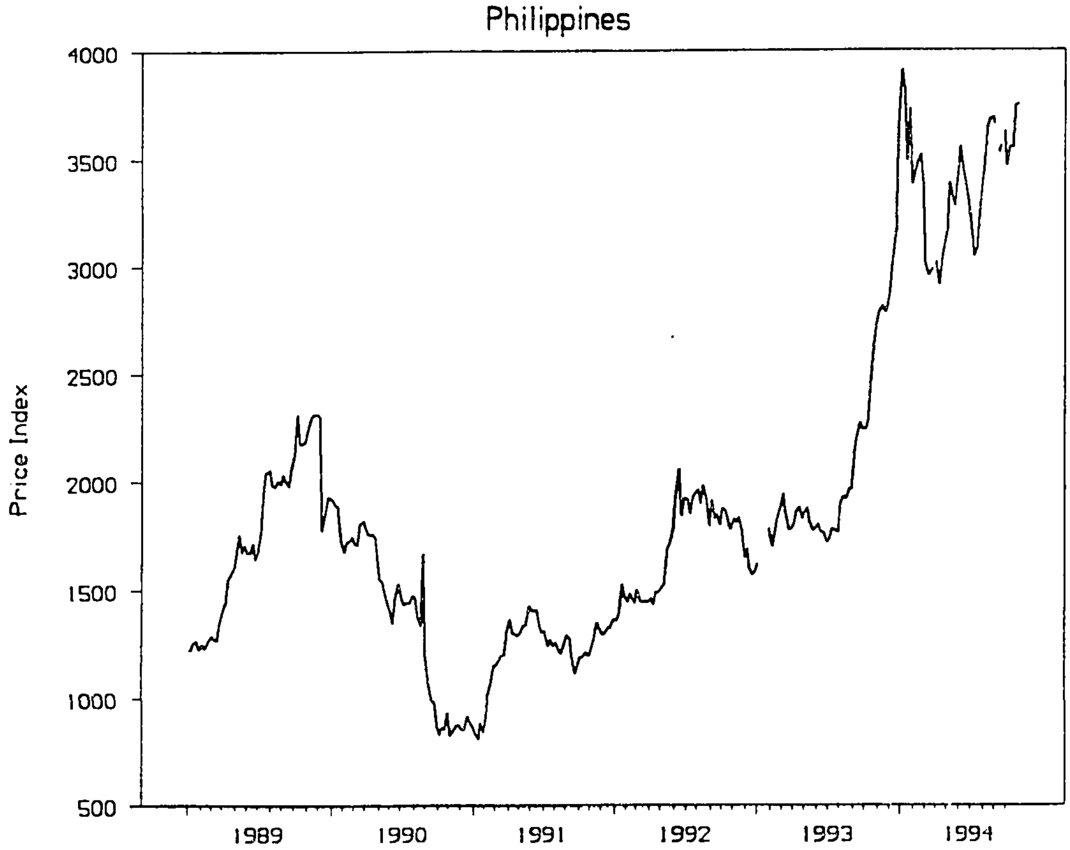
1994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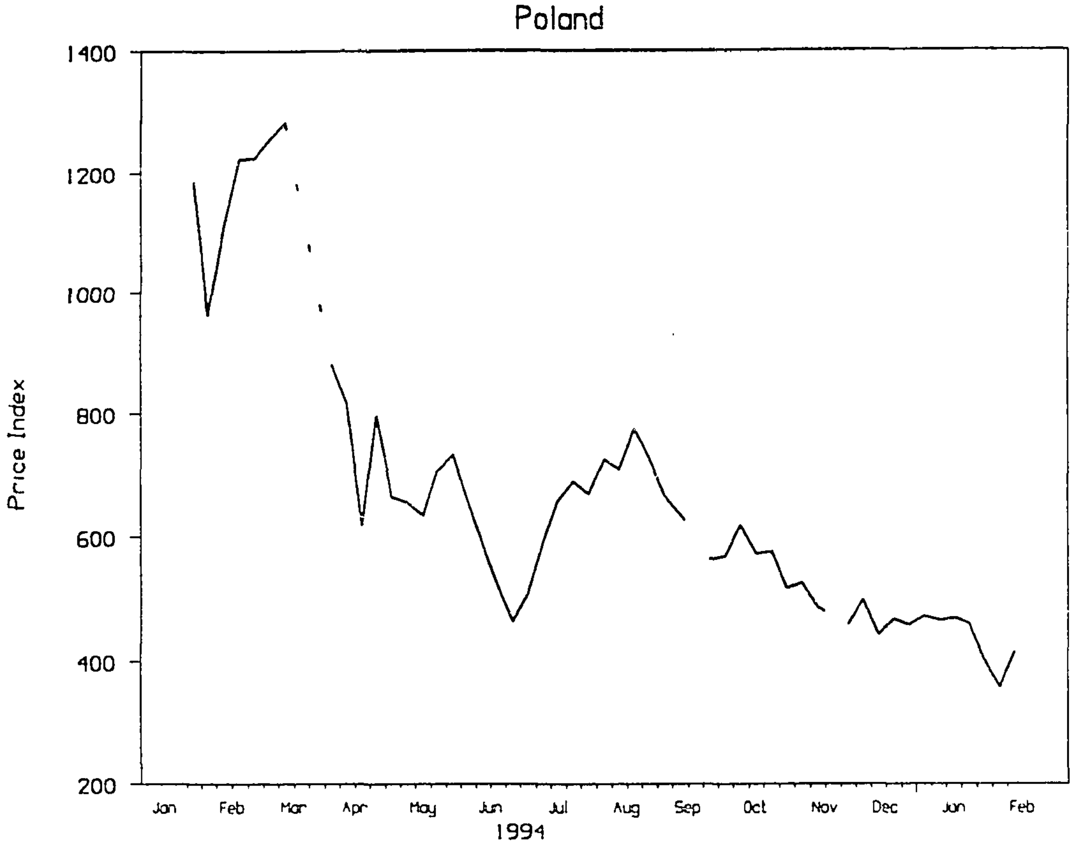
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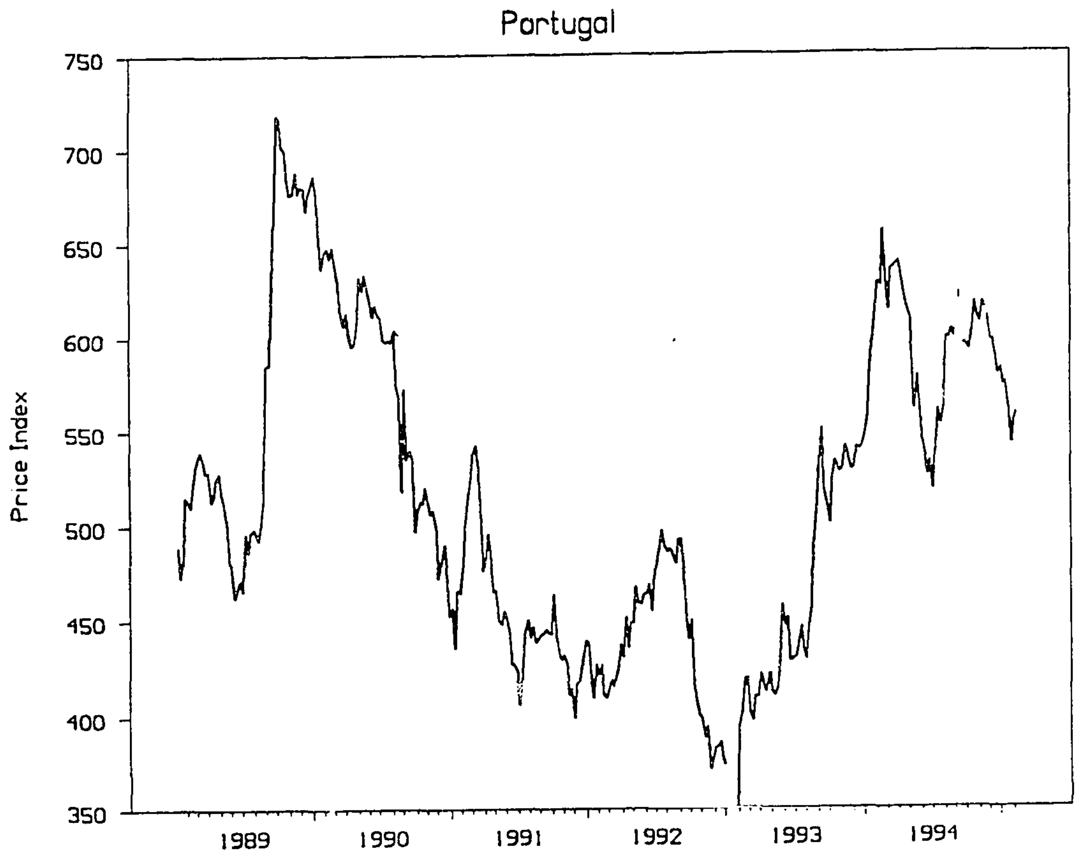
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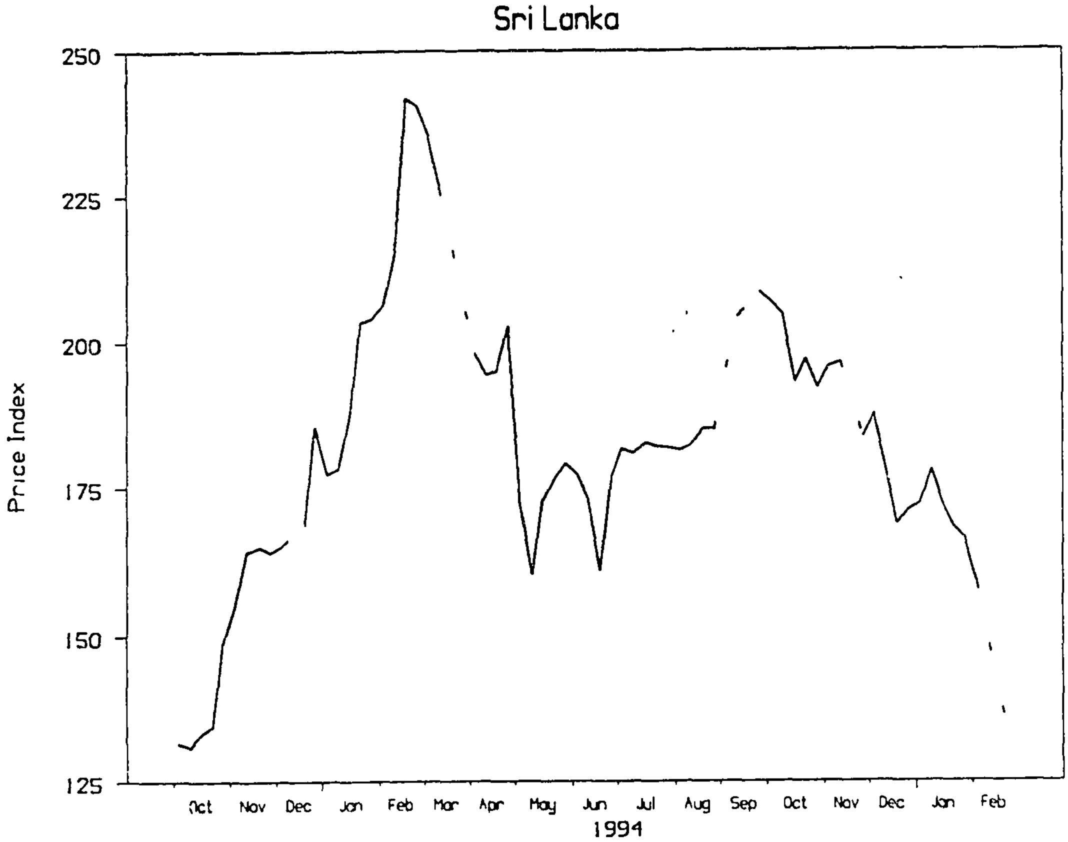
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Price Index
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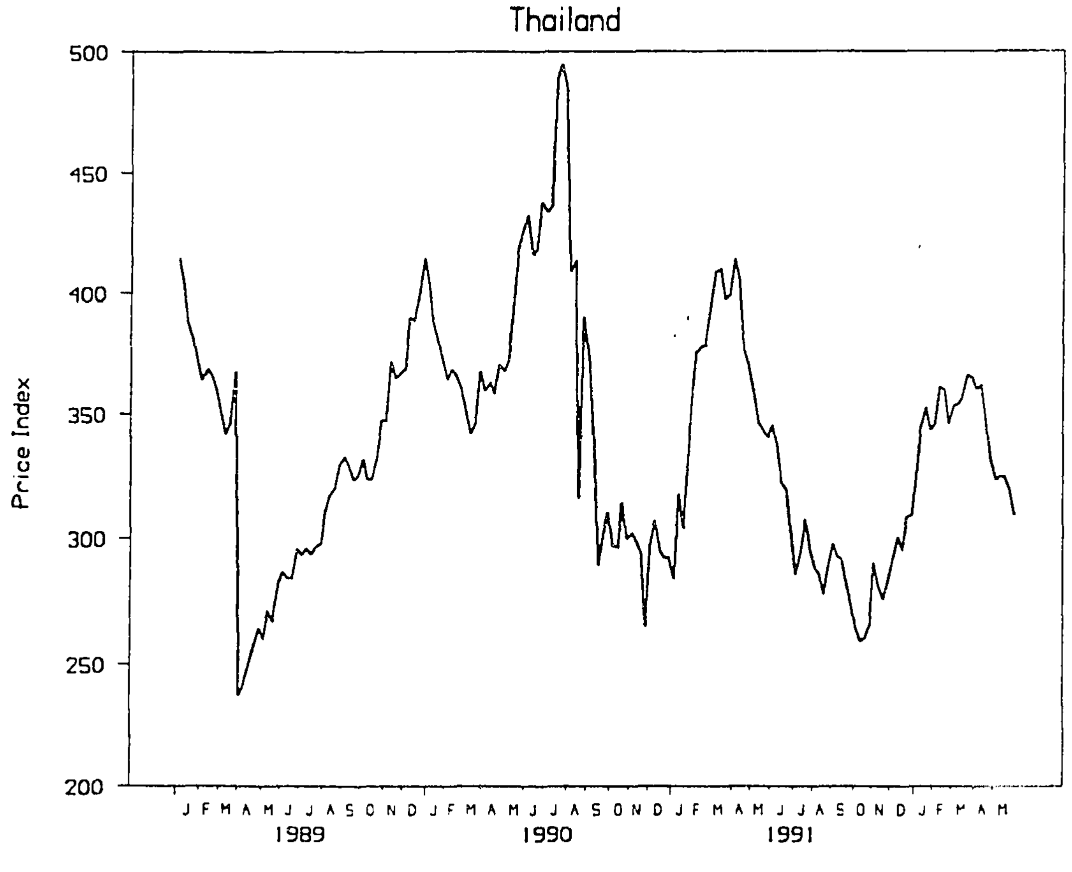
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1989
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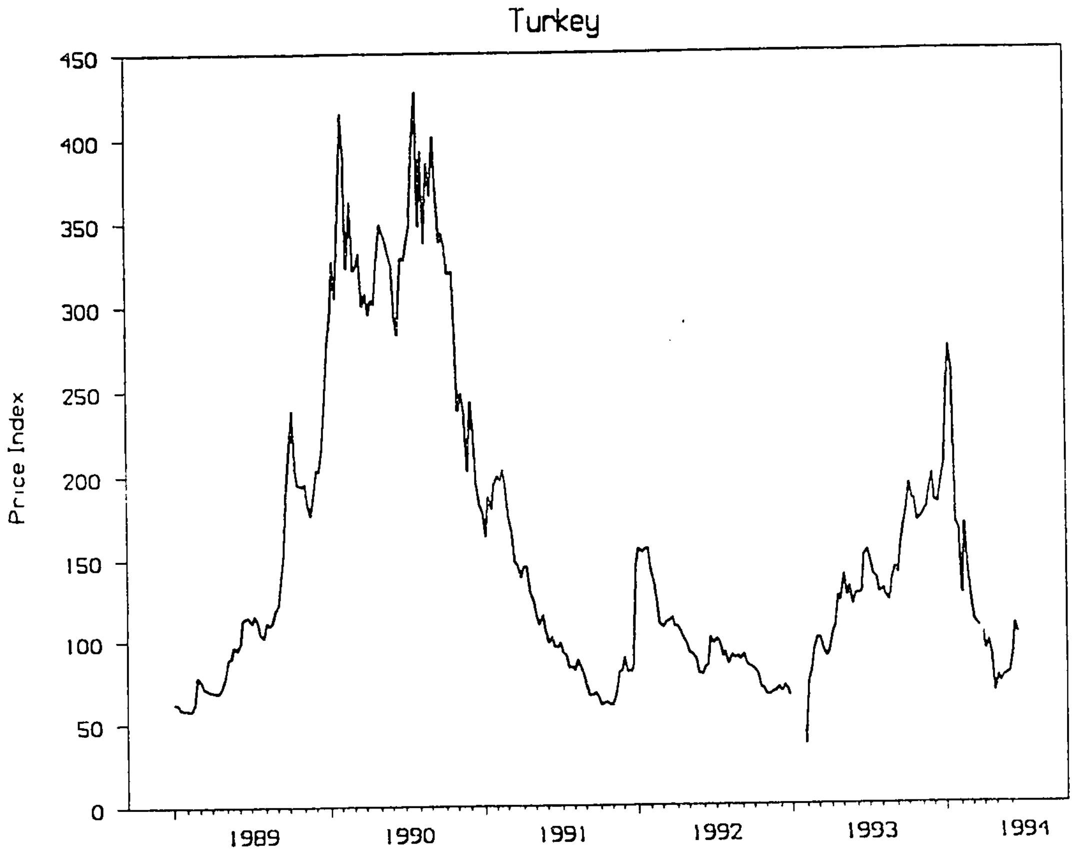
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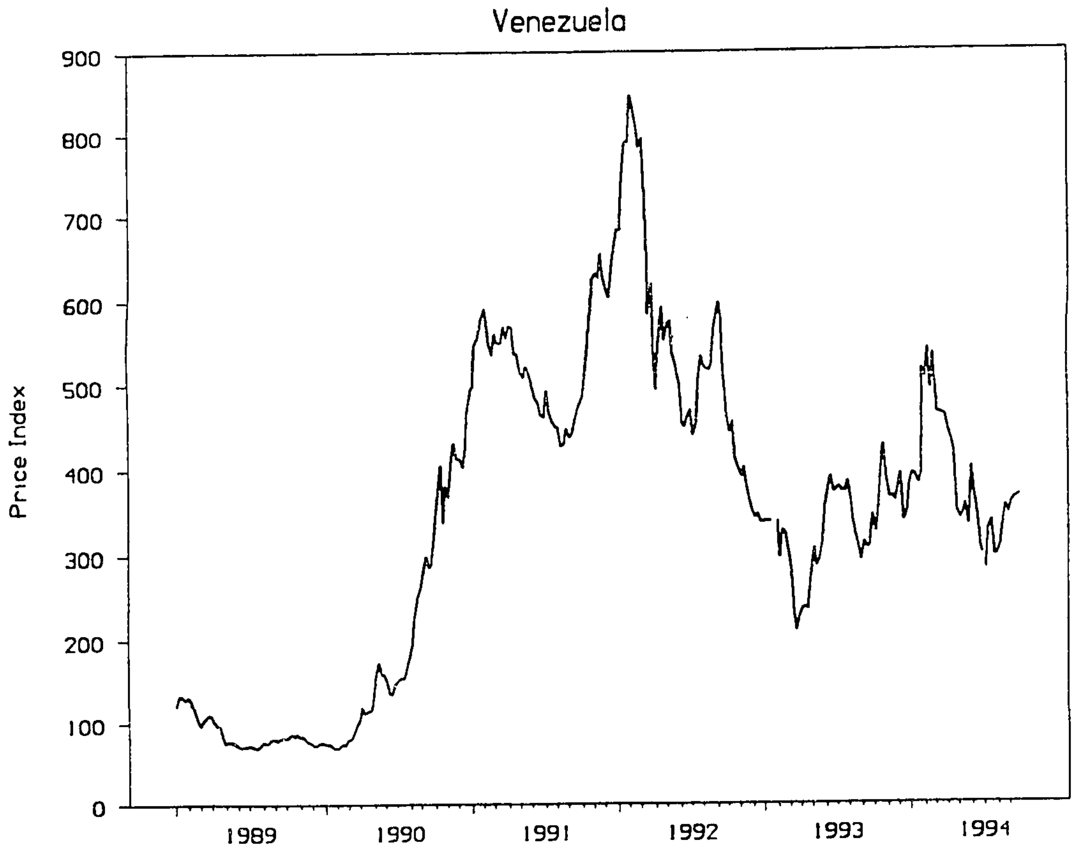
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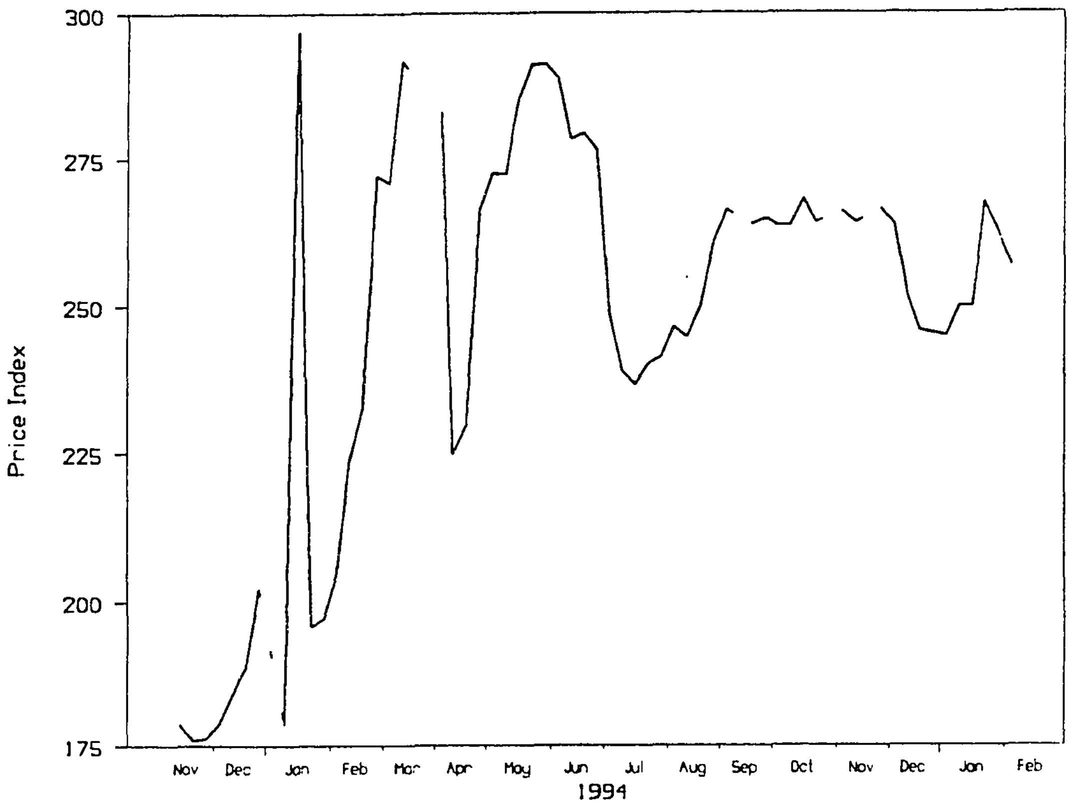
1994

Zimbabwe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Price Index
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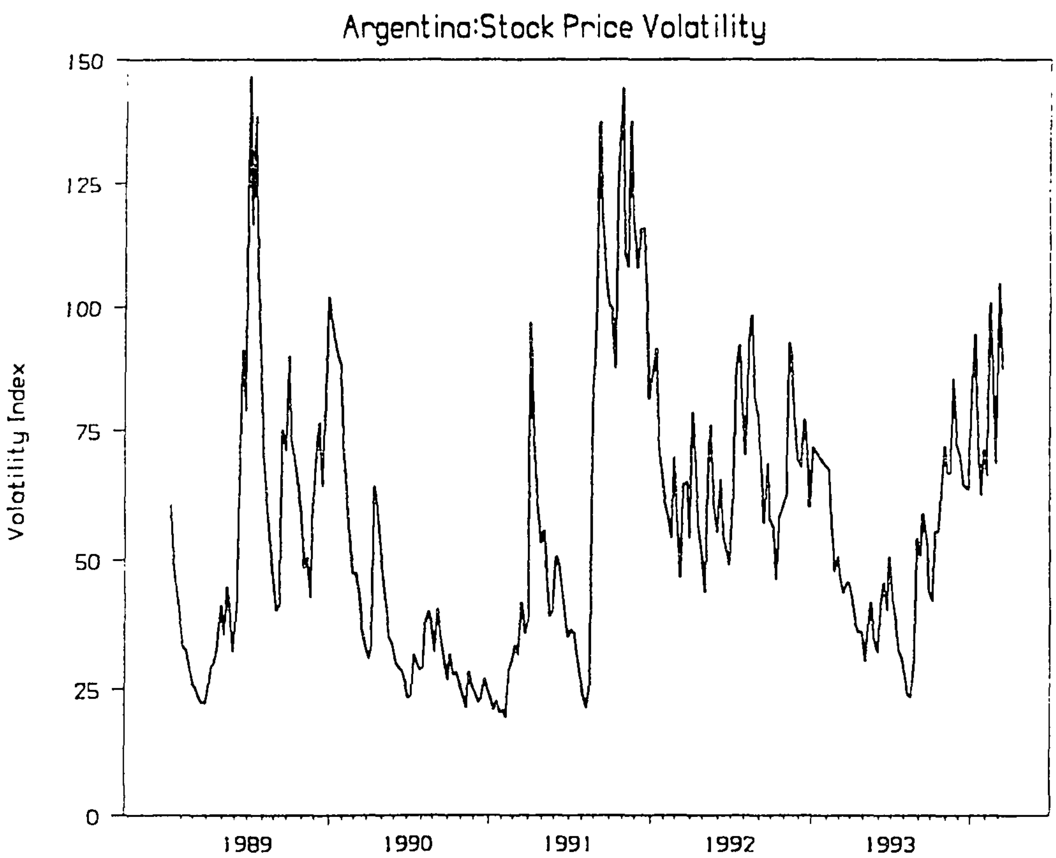
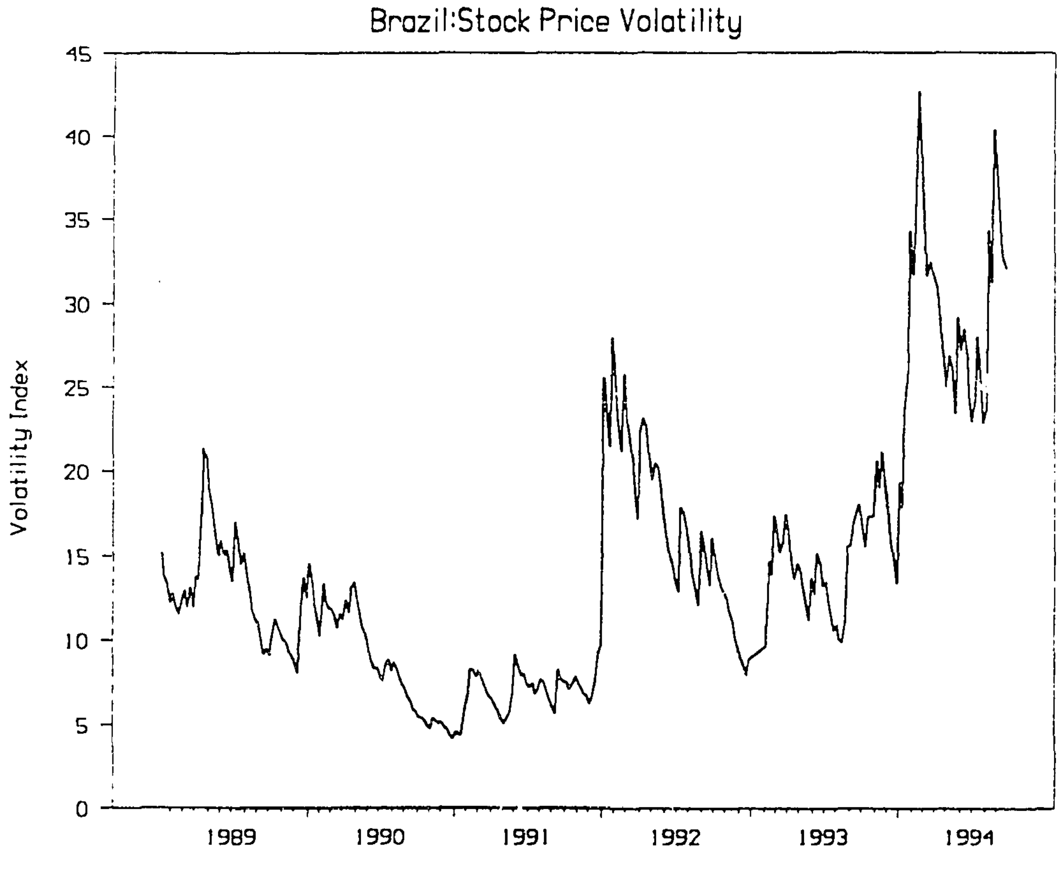
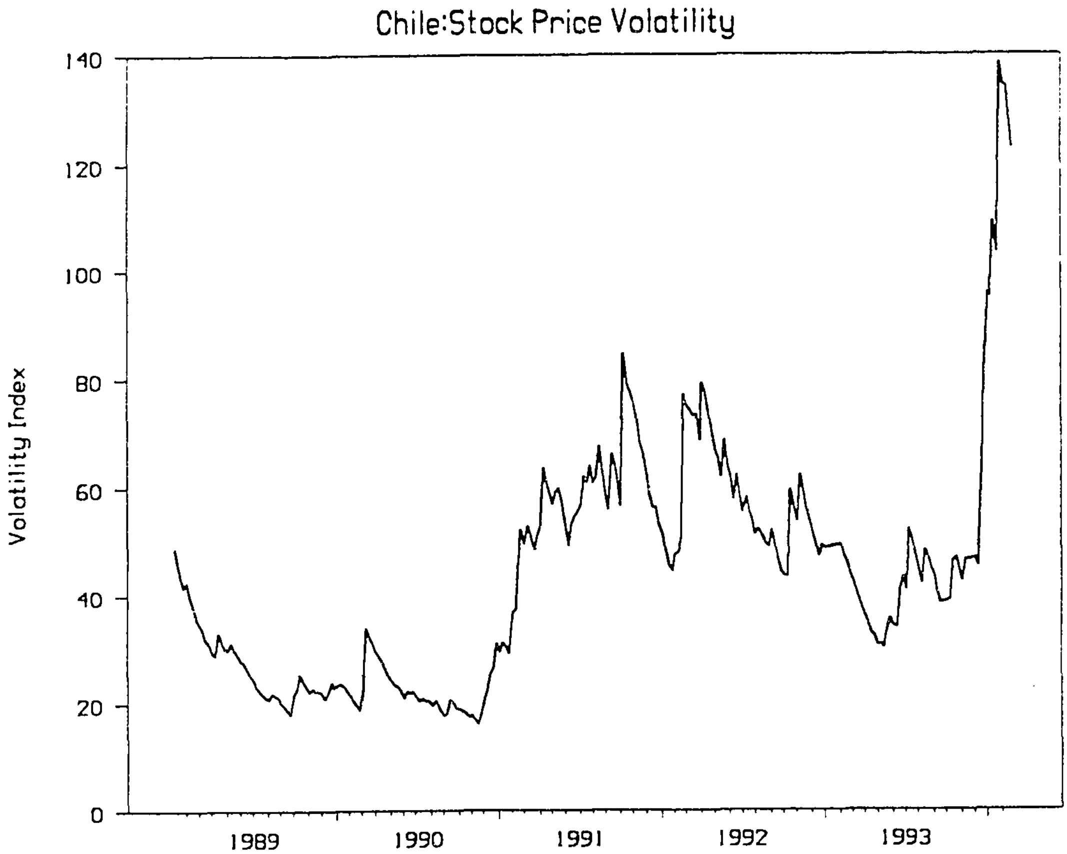
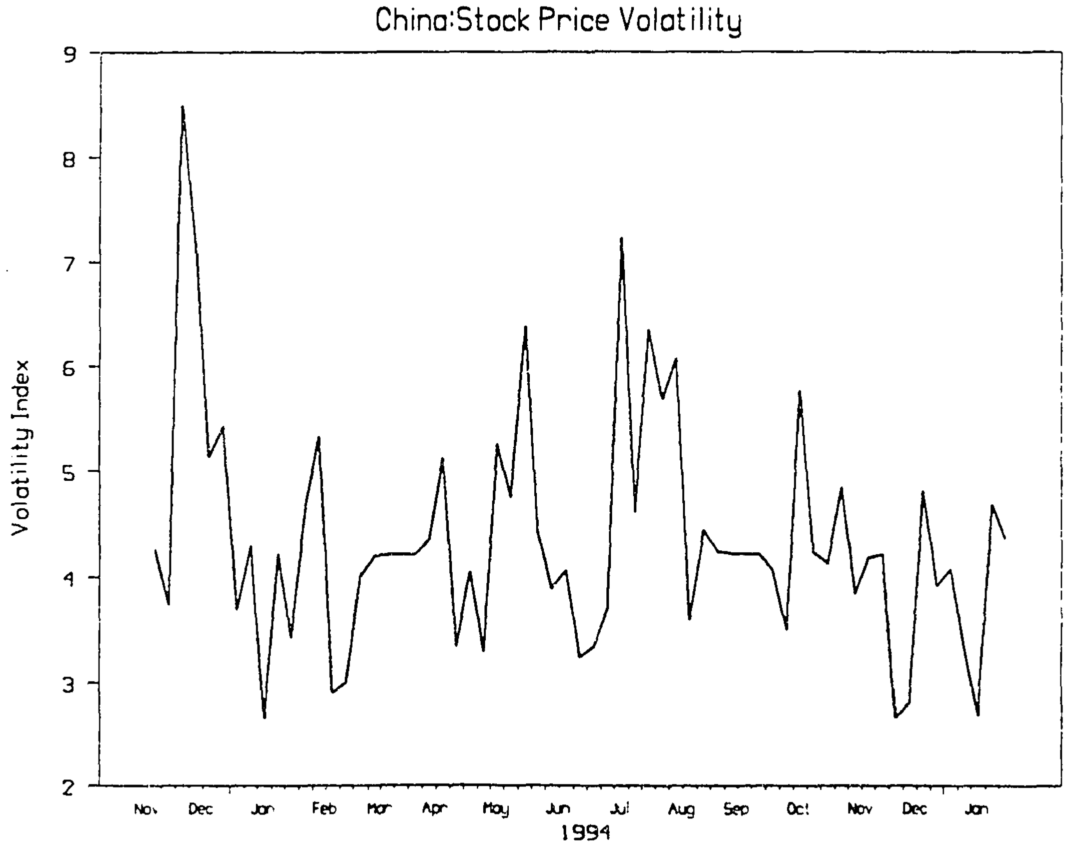
Nov
Dec
Jan
Feb
1994

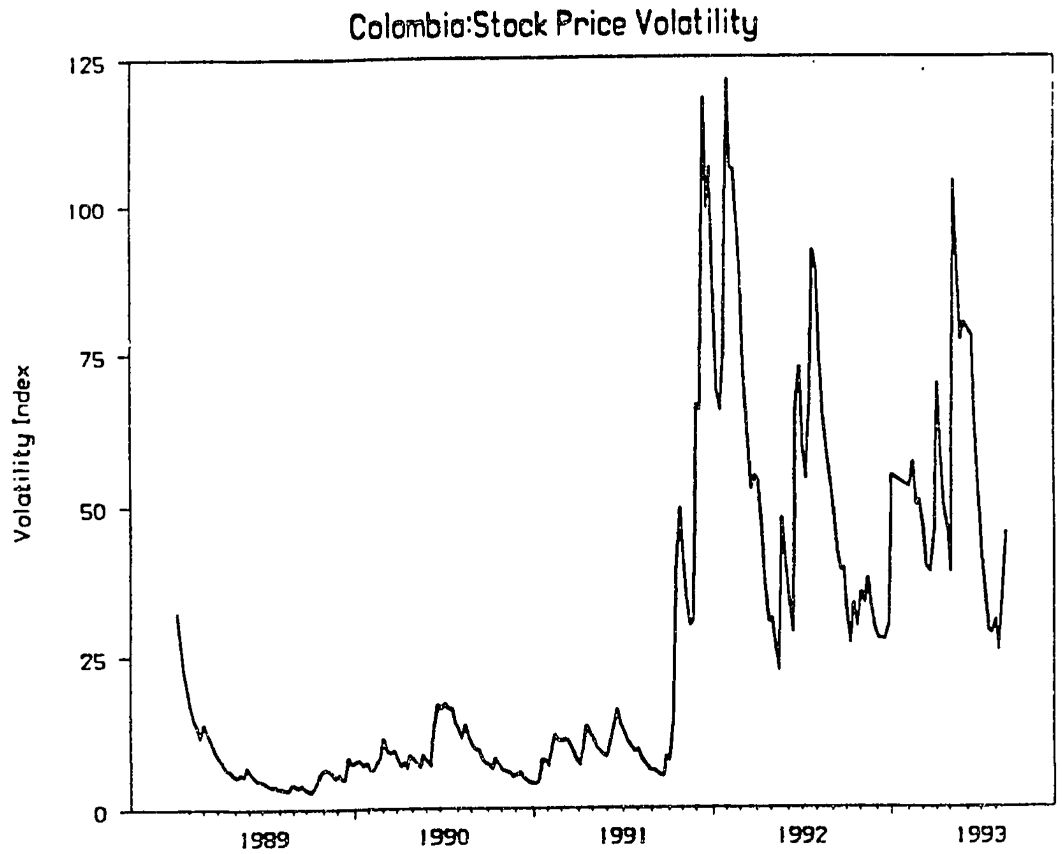
2. Stock Price Volatility

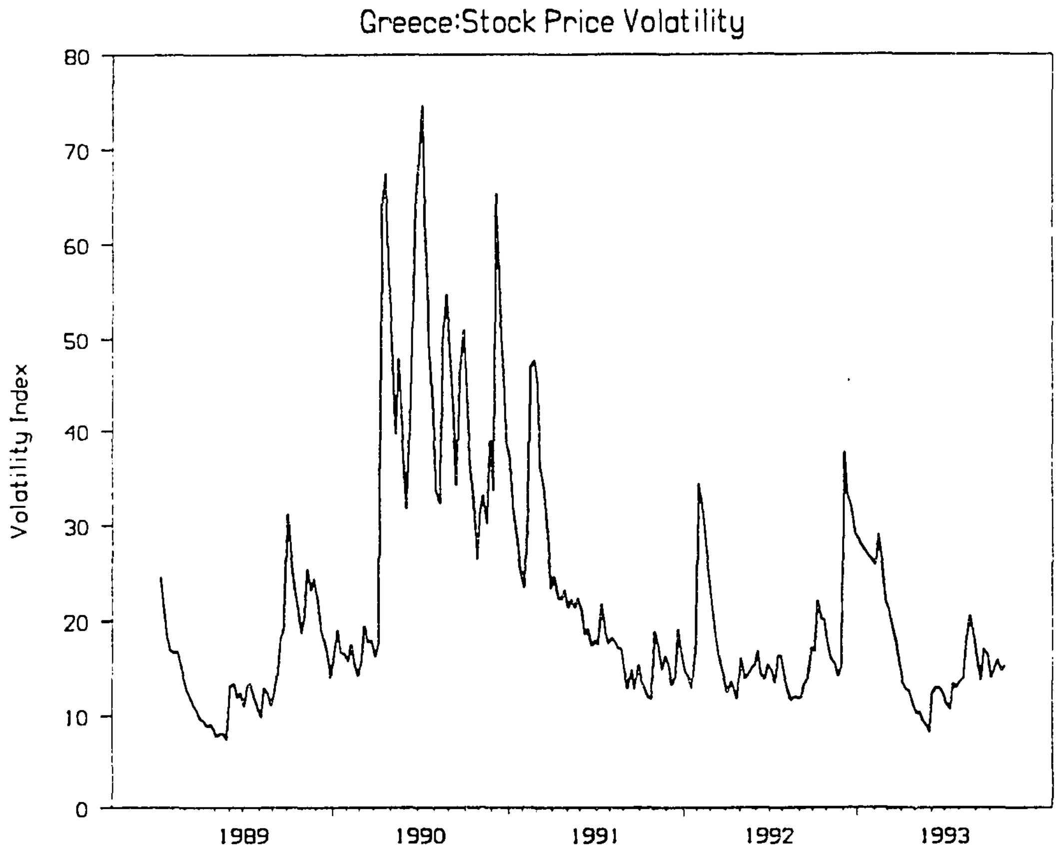


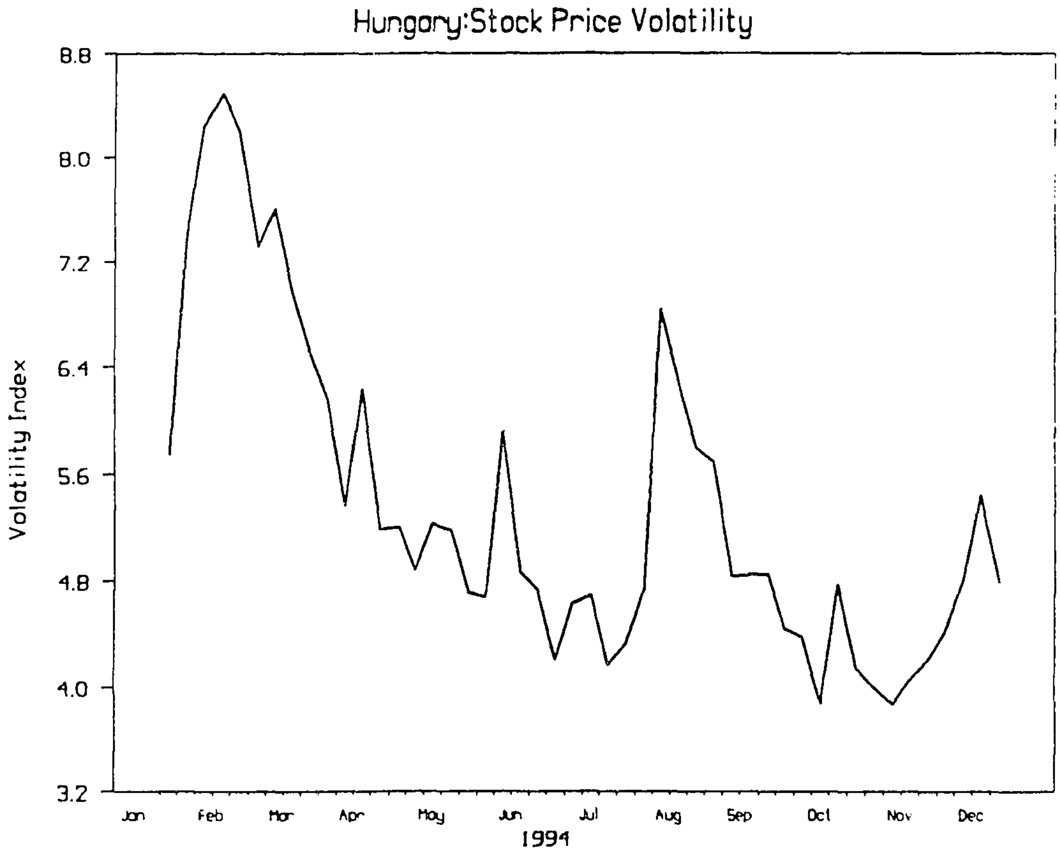

Brazil:Stock Price Volatility
Volatility Index
45
40
35
30
25
20
15
10
5
0
1989
1990
1991
1992
1993
1994

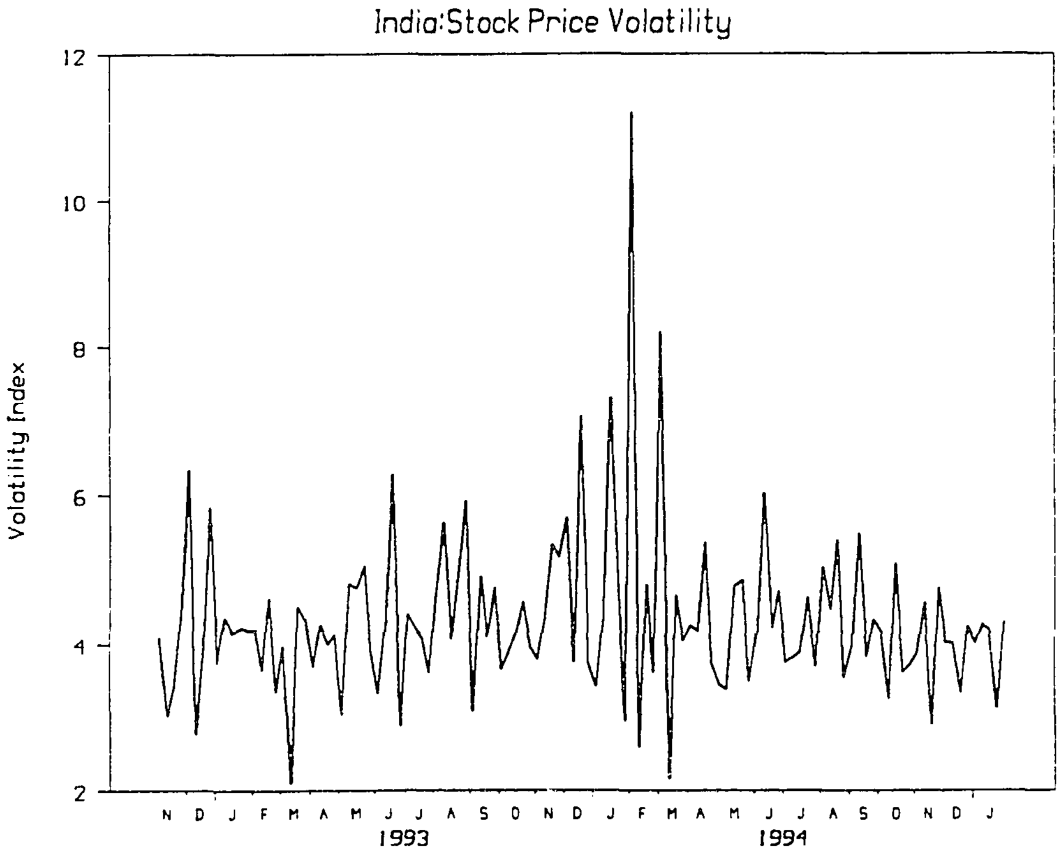

Chile:Stock Price Volatility
Volatility Index
140
120
100
80
60
40
20
0
1989
1990
1991
1992
1993

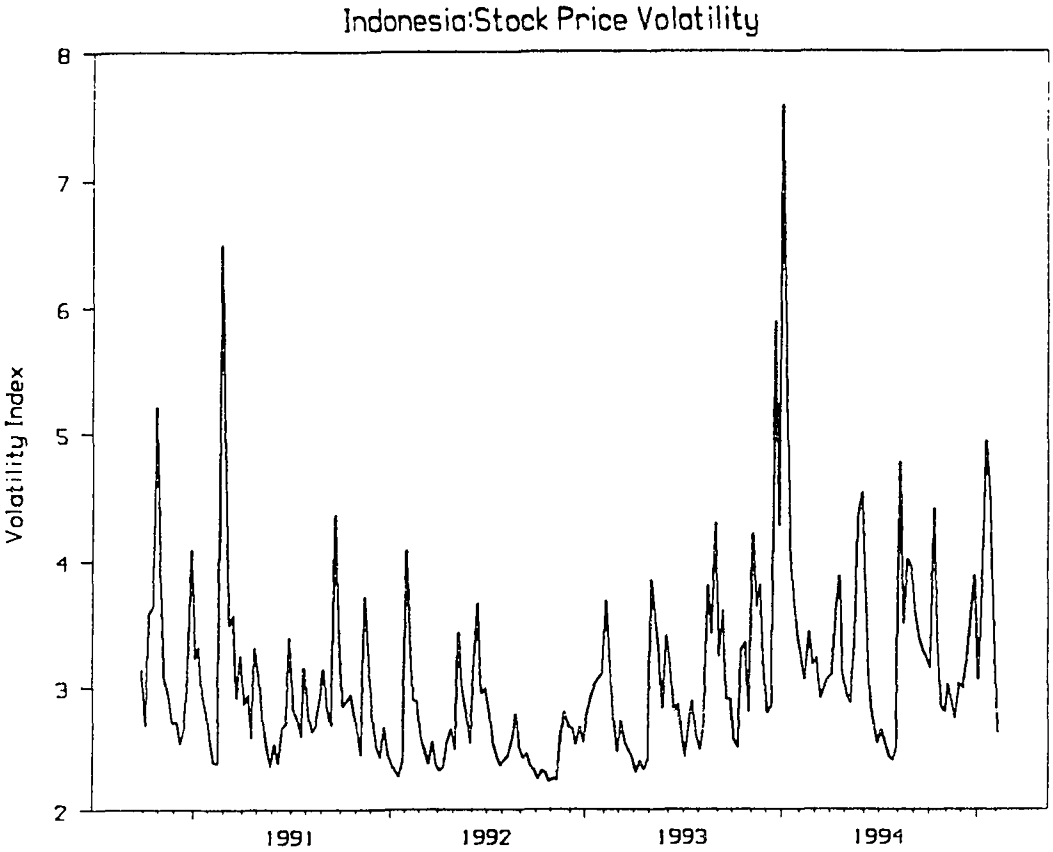

China:Stock Price Volatility
Volatility Index
9
8
7
6
5
4
3
2
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
1994

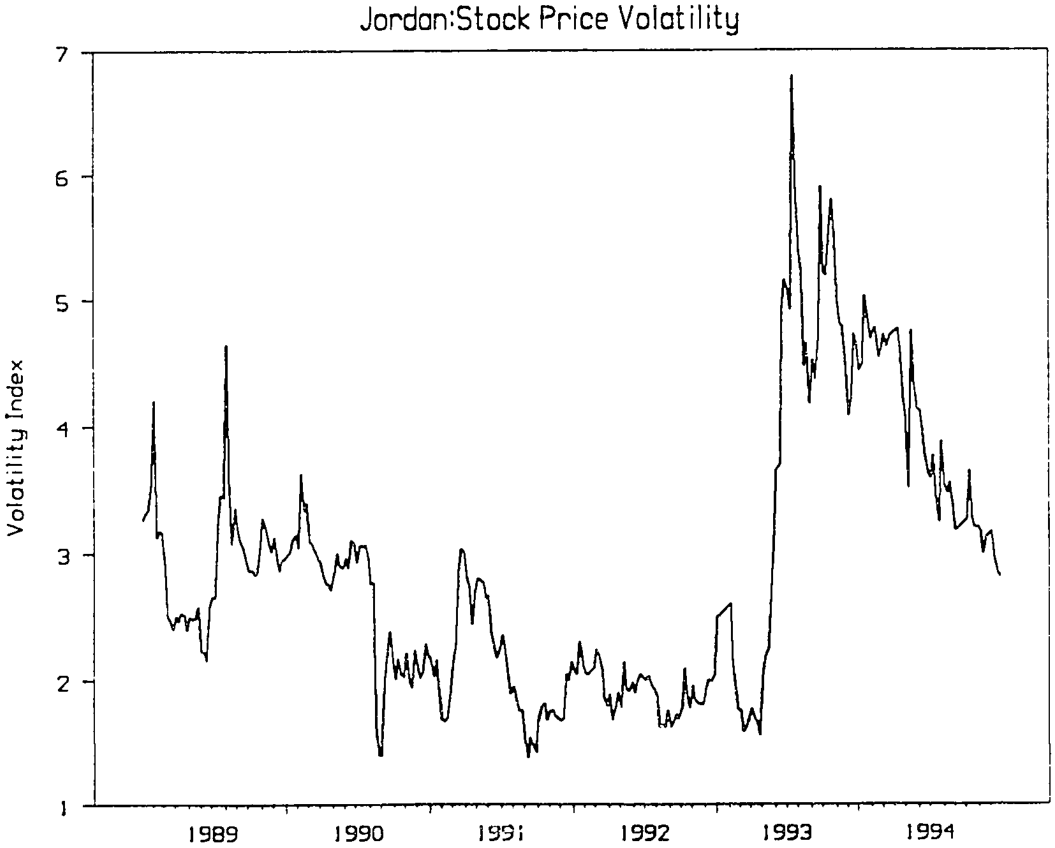

Colombia:Stock Price Volatility
125
100
75
50
25
0
Volatility Index
1989
1990
1991
1992
1993

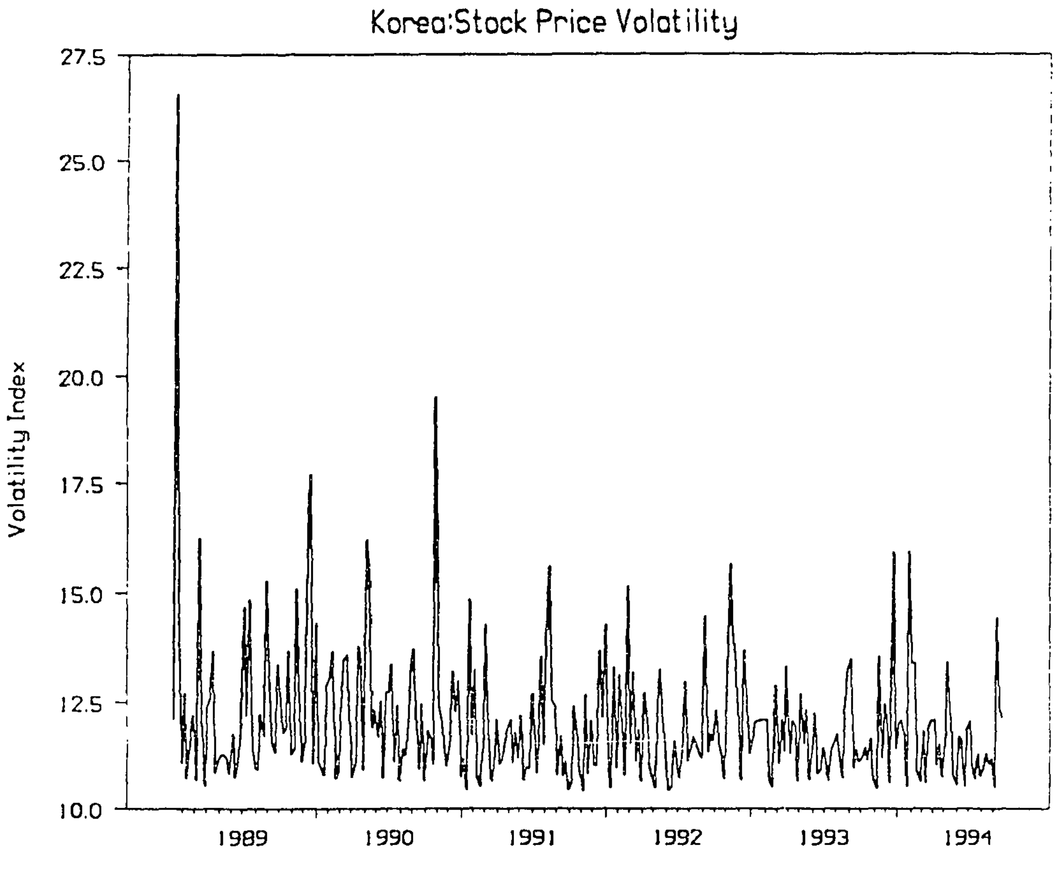

Greece:Stock Price Volatility
80
70
60
50
40
30
20
10
0
Volatility Index
1989
1990
1991
1992
1993

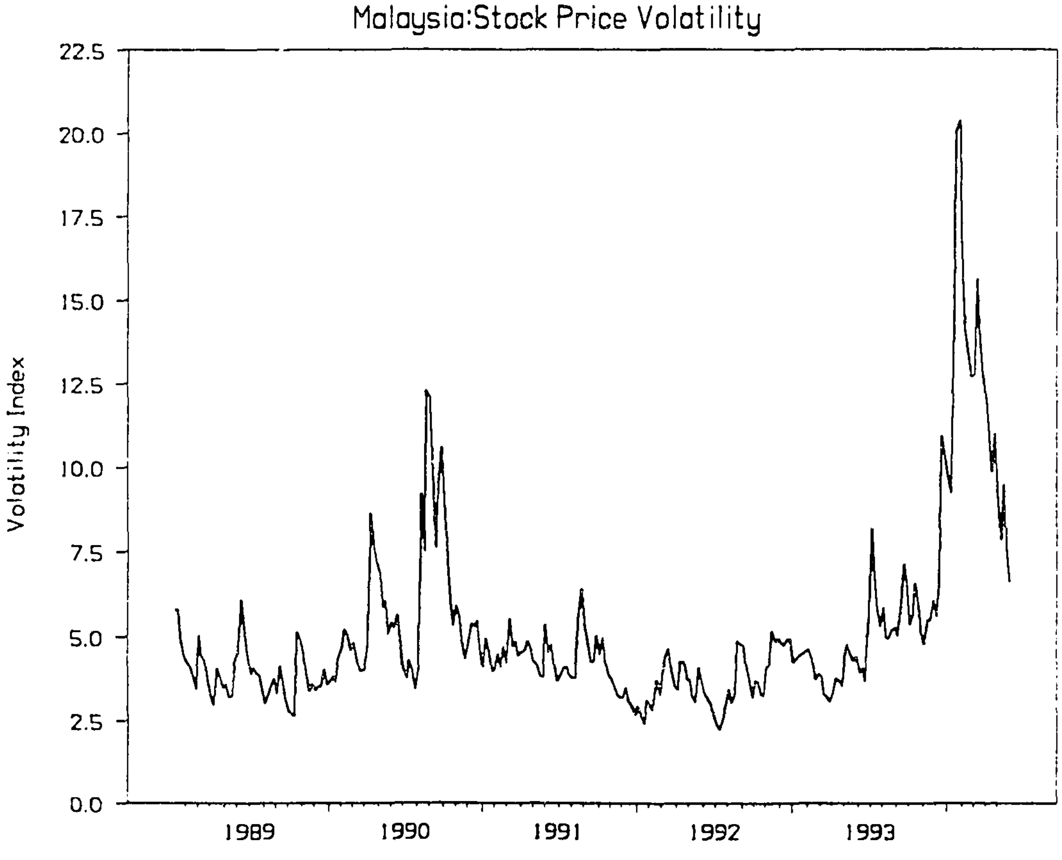

Hungary:Stock Price Volatility
8.8
8.0
7.2
6.4
5.6
4.8
4.0
3.2
Volatility Index
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
1994

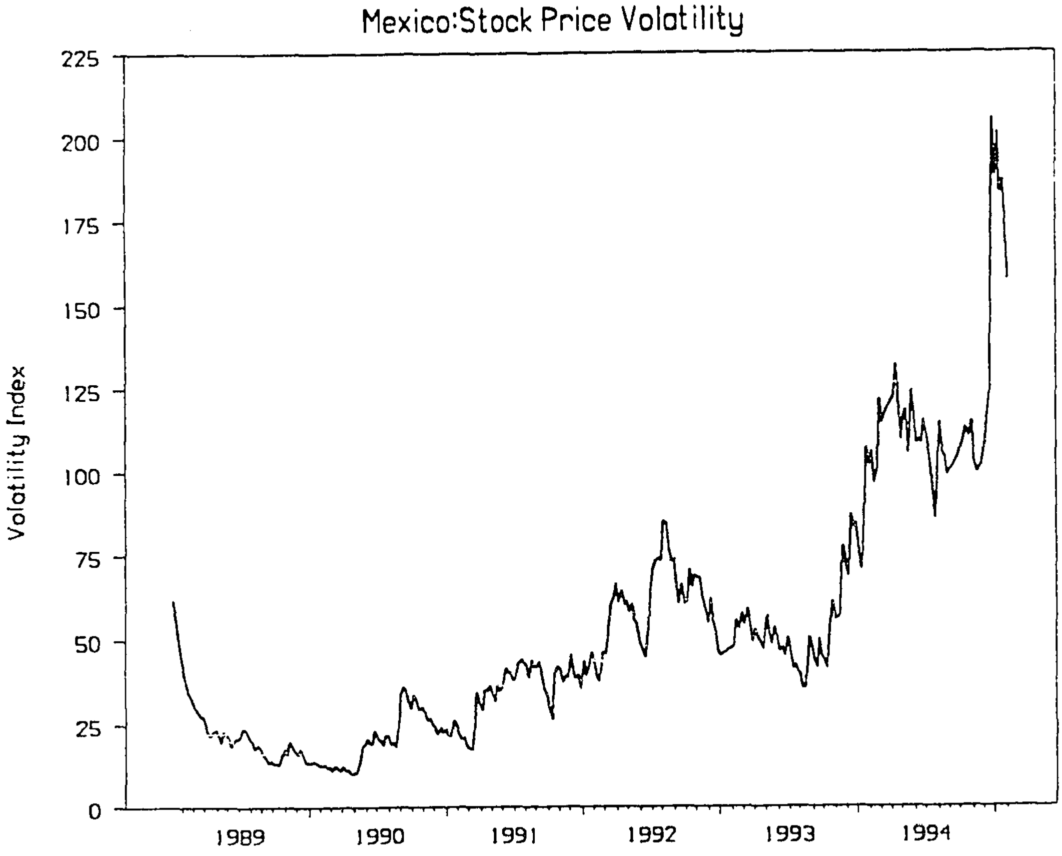

India:Stock Price Volatility
Volatility Index
12
10
8
6
4
2
N D J F M A M J J A S O N D J F M A M J J A S O N D J
1993
1994


Indonesia:Stock Price Volatility
Volatility Index
8
7
6
5
4
3
2
1991
1992
1993
1994

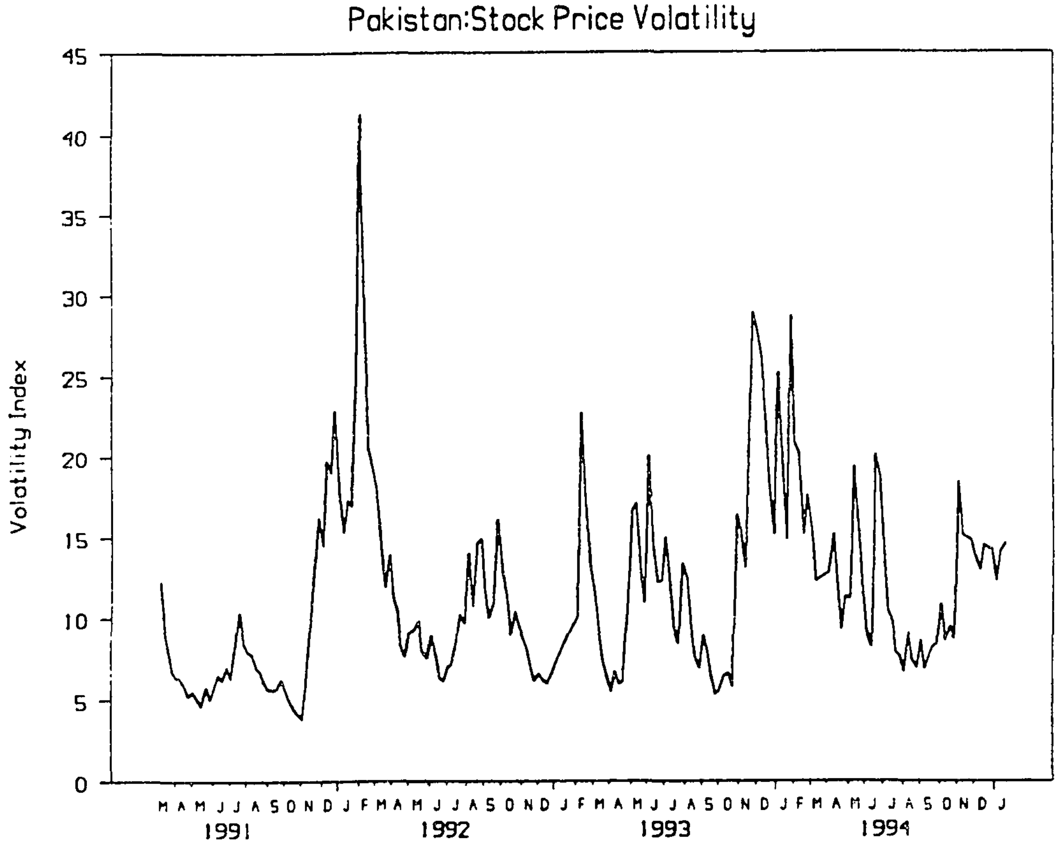

Jordan:Stock Price Volatility
Volatility Index
7
6
5
4
3
2
1
1989
1990
1991
1992
1993
1994

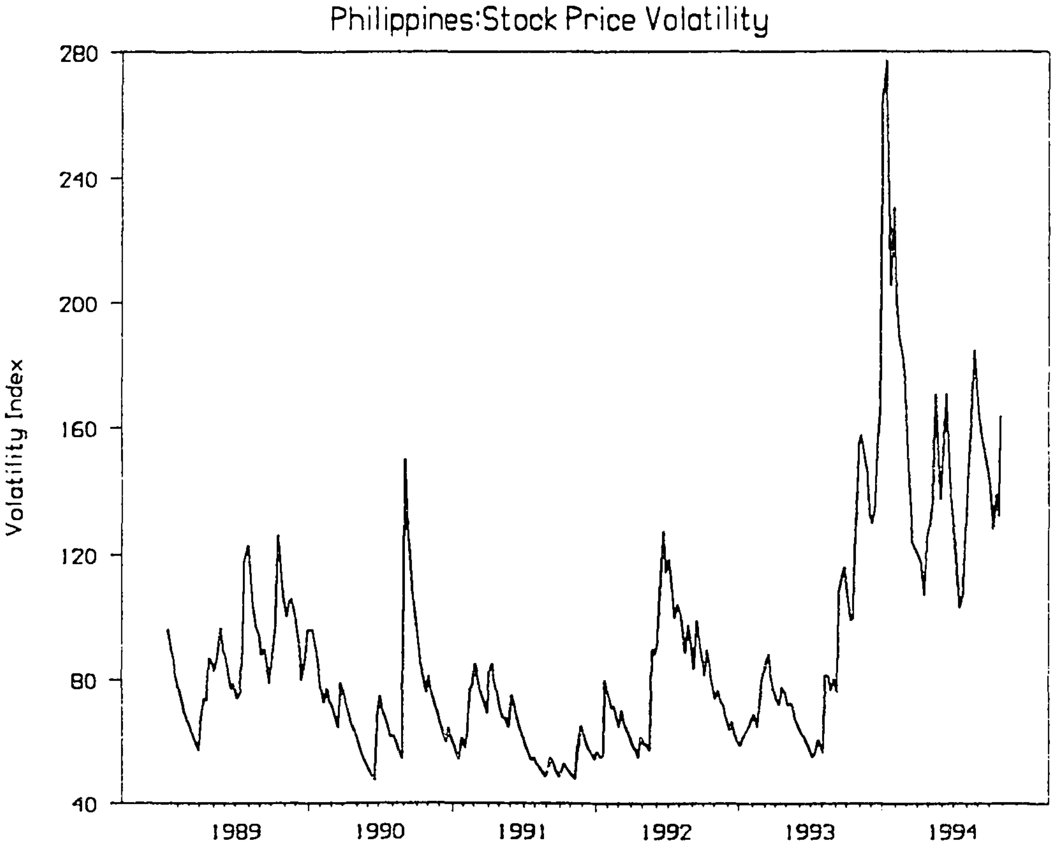

Korea:Stock Price Volatility
27.5
25.0
22.5
20.0
17.5
15.0
12.5
10.0
Volatility Index
1989
1990
1991
1992
1993
1994


Malaysia:Stock Price Volatility
Volatility Index
22.5
20.0
17.5
15.0
12.5
10.0
7.5
5.0
2.5
0.0
1989
1990
1991
1992
1993

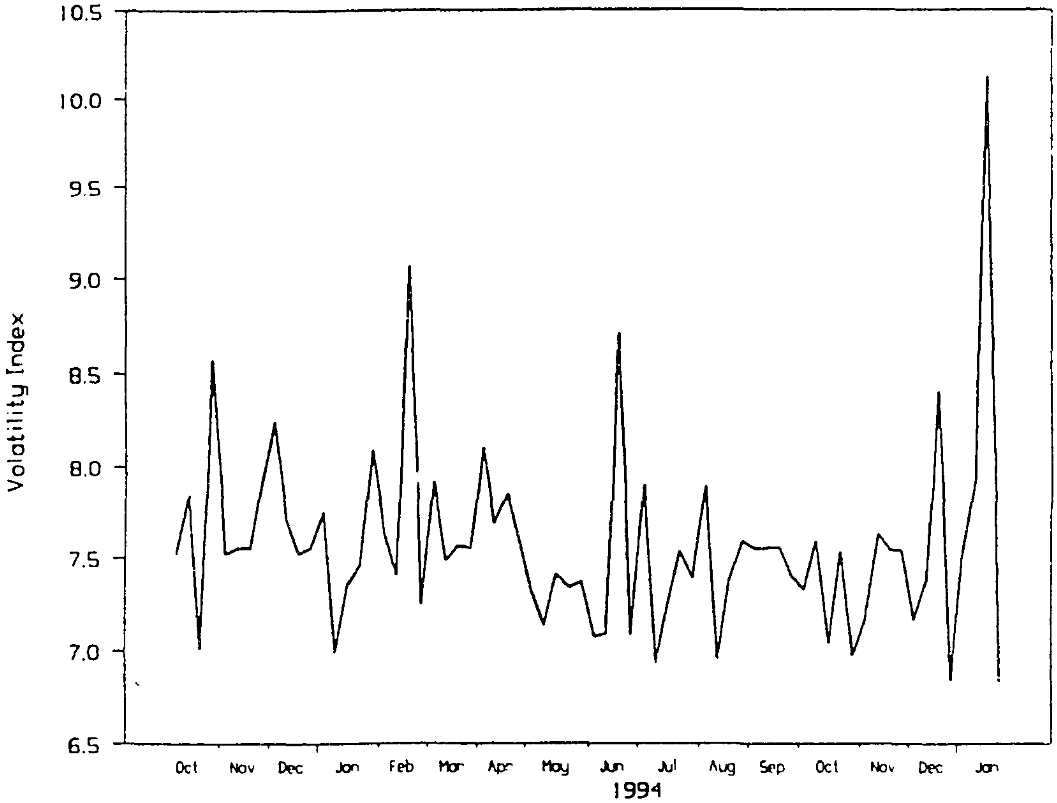


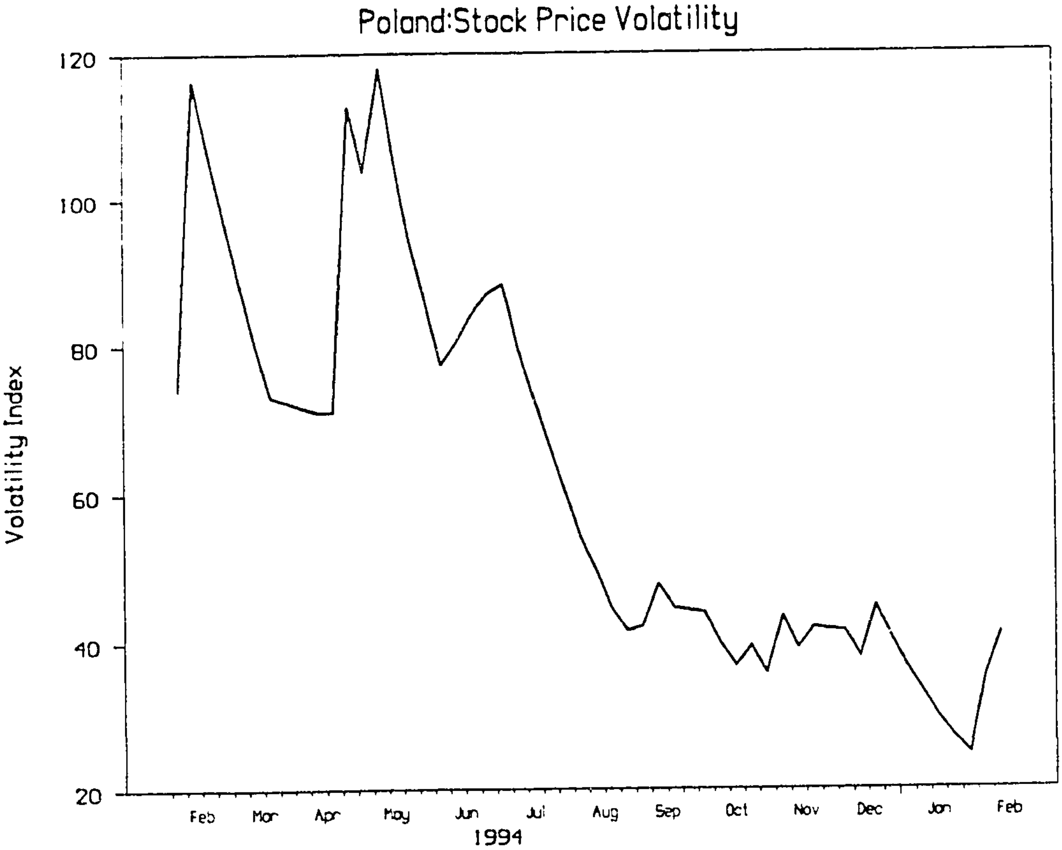
Mexico:Stock Price Volatility
225
200
175
150
125
100
75
50
25
0
Volatility Index
1989
1990
1991
1992
1993
1994

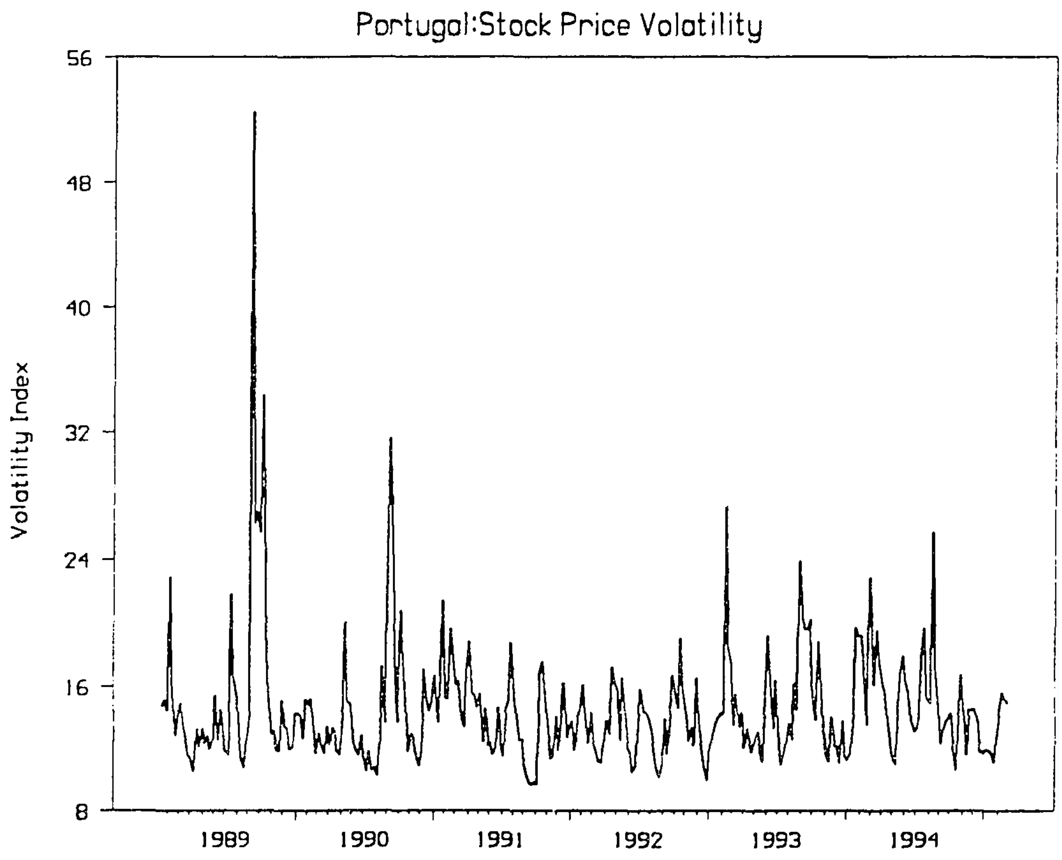

Pakistan:Stock Price Volatility
Volatility Index
45
40
35
30
25
20
15
10
5
0
M A M J J A S O N D J F M A M J J A S O N D J F M A M J J A S O N D J F M A M J J A S O N D J
1991
1992
1993
1994

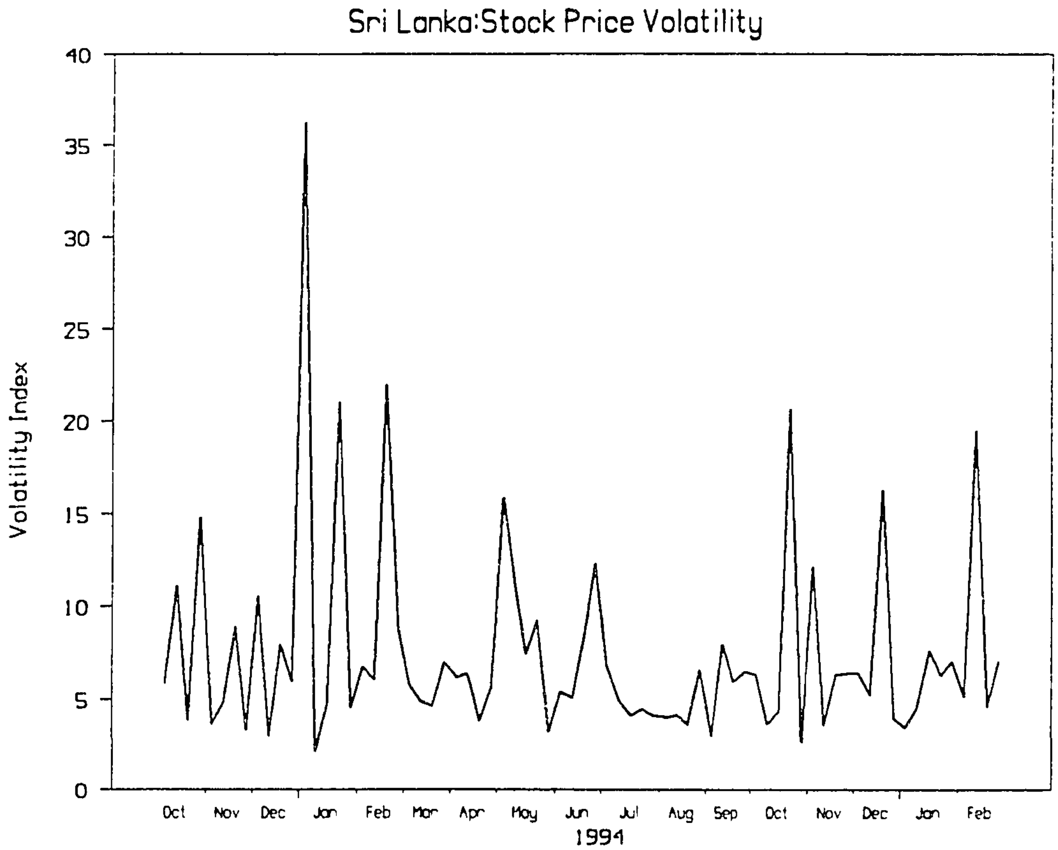

Philippines:Stock Price Volatility
Volatility Index
280
240
200
160
120
80
40
1989
1990
1991
1992
1993
1994

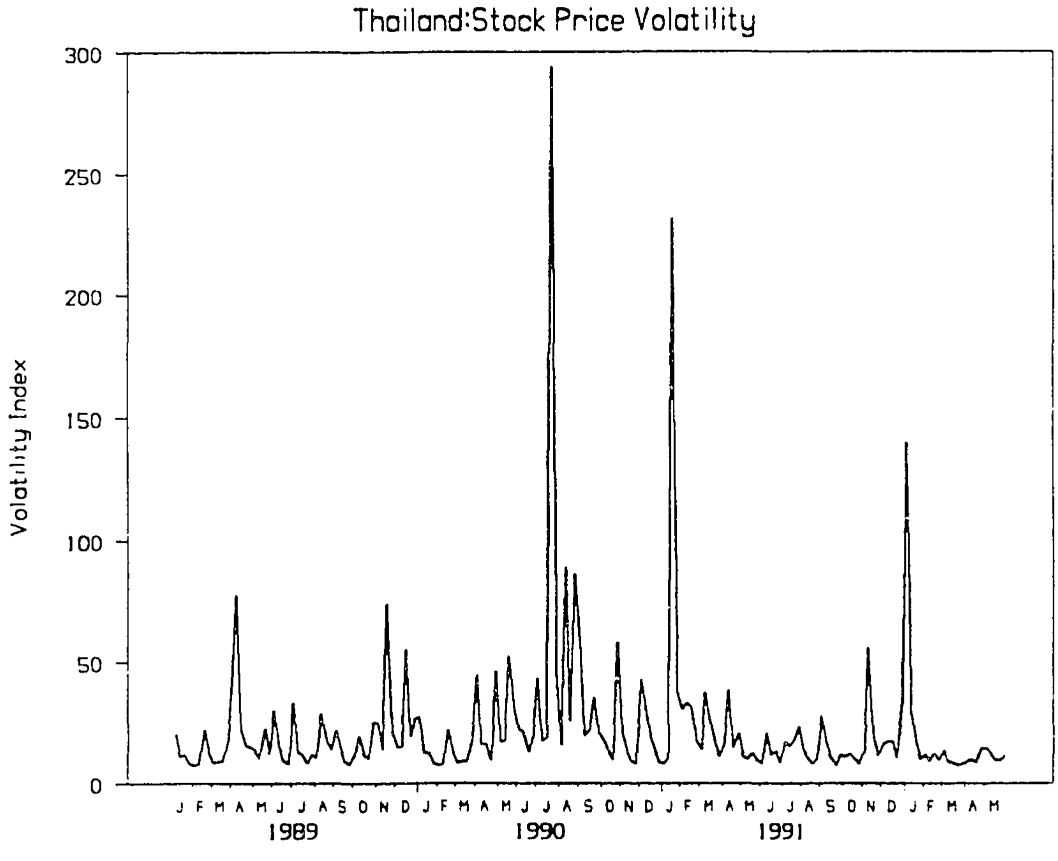
Peru:Stock Price Volatility

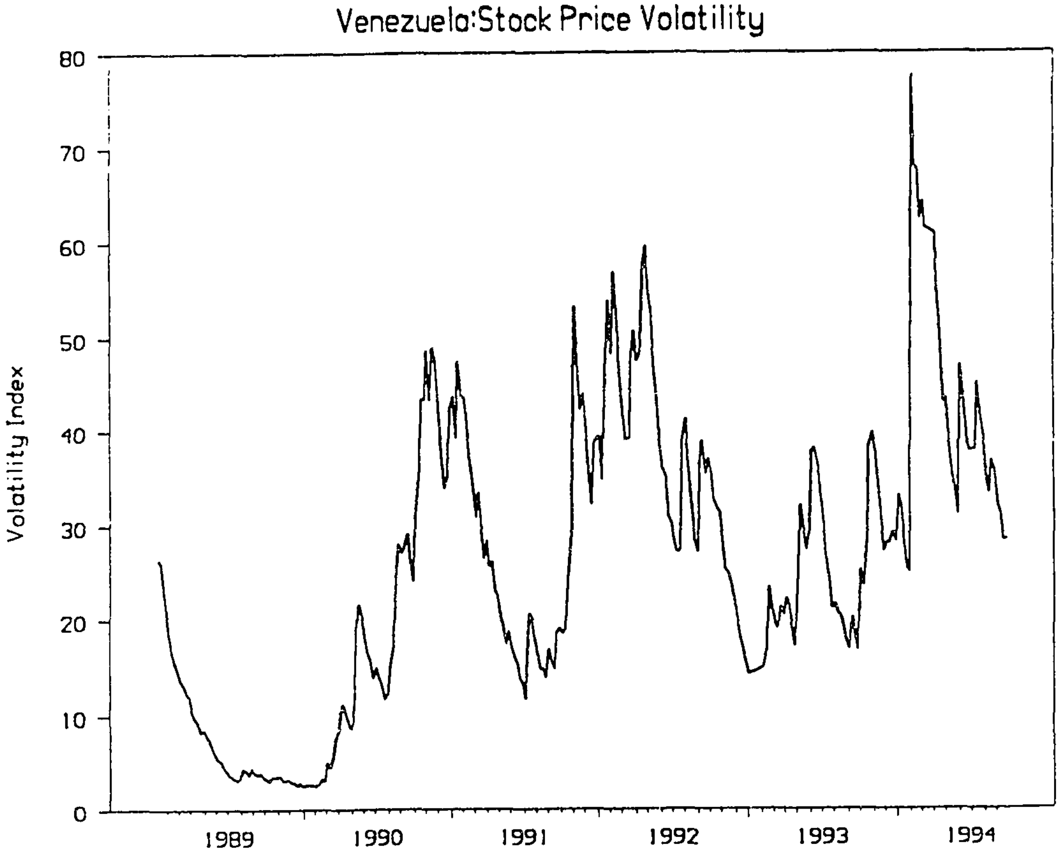


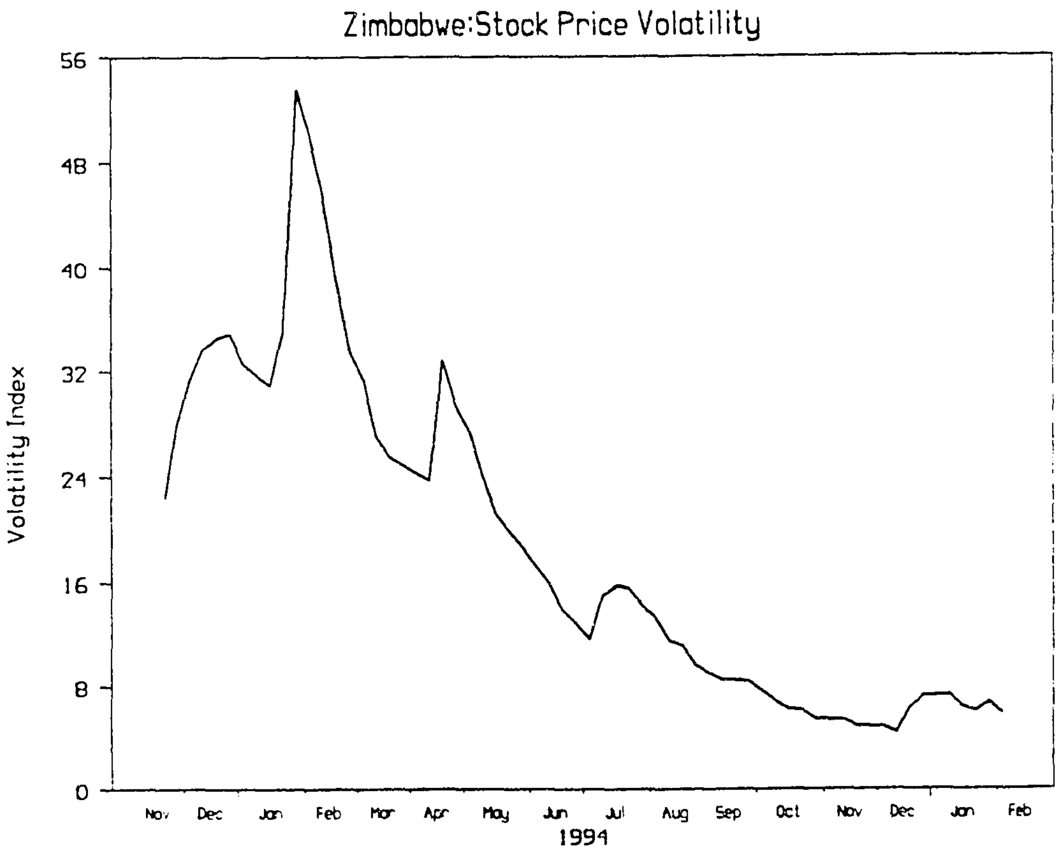

Poland:Stock Price Volatility
120
100
80
60
40
20
Volatility Index
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
1994


Portugal:Stock Price Volatility
Volatility Index
56
48
40
32
24
16
8
1989
1990
1991
1992
1993
1994


Sri Lanka:Stock Price Volatility
Volatility Index
40
35
30
25
20
15
10
5
0
Oct
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
1994


Thailand:Stock Price Volatility
300
250
200
150
100
50
0
Volatility Index
J F M A M J J A S O N D J F M A M J J A S O N D J F M A M J J A S O N D J F M A M
1989
1990
1991


Venezuela:Stock Price Volatility
80
70
60
50
40
30
20
10
0
Volatility Index
1989
1990
1991
1992
1993
1994



Zimbabwe:Stock Price Volatility
Volatility Index
56
48
40
32
24
16
8
0
Nov
Dec
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Jan
Feb
1994

Table 1

Dates are 1989-1994 unless noted otherwise, where data were only available for the dates given.

Yule-Walker estimates

Dependent variable=Log(Stock price volatility)

Country	intercept	+b1log of short-term interest rate	+b2log of U.S. Tbill	+b3 log of exchange rate	+b4 % change in ca	+b5 % ch. in def/surplus
(p-values are given in parentheses)						
1. Argentina*	1.03	.00035	-.484	.082	-.00378	.00127
	(.8644)	(.6827)	(.0490)	(.6902)	(.2908)	(.5810)
2. Brazil*						
	.875	-.004	-.286	.02	.0028	
	(.8487)	(.4907)	(.1995)	(.9025)	(.0984)	
3. Chile	-6.24	-.07	-.139	-.86	-2.72E-6	
	(.1573)	(.1834)	(.5372)	(.1152)	(.9933)	
4. China('93-'95)	-31.42	-	-2.83	-2.457	-.0029	
	(.1957)		(.0457)	(.3975)	(.0742)	

Yule-Walker estimates

Dependent variable=Log(Stock price volatility)

Country	intercept	+b1log of short-term interest rate	+b2log of U.S. Tbill	+b3 log of exchange rate	+b4 % change in ca	+b5 % ch. in def/surplus
(p-values are given in parentheses)						
5. Colombia('89-'93)	1.72	-1.46	-1.7	.000091	-.00001	.002
	(.8742)	(.2640)	(.01)	(.9999)	(.95)	(.2831)
6. Greece*('89-'93)	-9.04	.56	.71	2.78	-.0004	.18
	(.0080)	(.7039)	(.0003)	(.0075)	(.6222)	(.9354)
7. Hungary ('93-'94)	-350.00	14.19	1.044	-35.7	-	-
	(.1141)	(.0223)	(.7216)	(.2449)		
8. India('92-'95)	6.79	-.28	-1.005	.496	-	-
	(.2258)	(.06)	(.1162)	(.362)		

Yule-Walker estimates

Dependent variable=Log(Stock price volatility)

Country	intercept	+b1log of short-term interest rate	+b2log of U.S. Tbill	+b3 log of exchange rate	+b4 % change in ca	+b5 % ch. in def/surplus
(p-values are given in parentheses)						
9. Indonesia*('90-'95)	1.48	.0067	.21	not	-.0061	-
	(.7288)	(.8286)	(.04)	included	(.2895)	
				because		
				it caused	multicollinearity	
10. Jordan*	-.24	-.16	.61	-.132	-.00026	-.00022
	(.8343)	(.3930)	(.1557)	(.8846)	(.56)	(.6828)
11. Korea	68.9	-1.665	-.34	4.3	-.014	.0002
	(.0007)	(.02)	(.5164)	(.1518)	(.2737)	(.9876)
12. Malaysia*	-12.9	.0009	-.07	-3.86	-.000015	-
	(.0321)	(.9128)	(.7371)	(.0124)	(.7180)	
13. Mexico*('89-'95)	10.85	-.66	-1.302	3.24	-.017	-.001
	(.0001)	(.0001)	(.0001)	(.0004)	(.4631)	(.7796)
14. Pakistan('91-'95)	-11.006	-.017	-.378	-.23	.00027	-
	(.3403)	(.7986)	(.5196)	(.9130)	(.8990)	

Yule-Walker estimates

Dependent variable=Log(Stock price volatility)

Country	intercept	+b1log of short-term interest rate	+b2log of U.S. Tbill	+b3 log of exchange rate	+b4 % change in ca	+b5 % ch. in def/surplus
(p-values are given in parentheses)						
15. Peru*('93-'95)	1.289 (.06)	.176 (.1181)	.074 (.3911)	-.4485 (.4636)	-	-.0024 (.0105)
16. Philippines	-7.22 (.1651)	-.03 (.8942)	-.0952 (.6475)	-.082 (.9222)	-.0003 (.5794)	-1.05E-6 (.9140)
17. Poland ('94-'95)	-2.3 (.8895)	1.8 (.2222)	-1.36 (.0001)	-1.34 (.1268)	-	-
18. Portugal('89-'95)	-.43 (.9011)	-.248 (.3126)	-.114 (.352)	-.3258 (.4006)	.00056 (.5156)	-
19. Sri Lanka*('93-'95)	39.99 (.4707)	.02 (.1471)	-.26 (.5249)	9.76 (.4944)	.0152 (.3716)	-
20.Thailand('89-'92)	-76.75 (.2687)	variable omitted because it caused multicollinearity.	3.7 (.1767)	-24.06 (.2712)	-.05 (.2323)	-

Yule-Walker estimates
Dependent variable=Log(Stock price volatility)

Country	intercept	+b1log of short-term interest rate	+b2log of U.S. Tbill	+b3 log of exchange rate	+b4 % change in ca	+b5 % ch. in def/surplus
(p-values are given in parentheses)						
21.Turkey	Estimate of Stock Price Volatility could not be fit.					
22.Venezuela	Yule-Walker model could not be fit.					
23. Zimbabwe ('93-'95)	21.15 (.00053)	-2.16 (.1846)	-1.94 (.0001)	.26 (.8151)	-.00036 (.8912)	-

* percentage changes for interest rate, exchange rate or export rate

Country	+log of exports	+b7inflation	+b8inflation squared	R-squared
1.Argentina*	.174	.00009	-4.615E-9	.83
	(.5540)	(.0467)	(.031)	
2.Brazil*	.087	.000197	-2.15E-8	.94
	(.6751)	(.177)	(.2584)	
3.Chile	.26	.031	-.00126	.97
	(.07)	(.5499)	(.3420)	
4.China('93-'95)	-1.69	-1.021	.023	.75
	(.0084)	(.6051)	(.5895)	
5. Colombia('89-'93)	-.024	.71	-.01	
	(.9518)	(.06)	(.08)	.95
6.Greece*('89-'93)	-.000143	-2.58E-12	1.07E-23	.87
	(.9194)	(.8182)	(.8531)	

Country	+log of exports	+b7inflation	+b8inflation squared	R-squared
7.Hungary('93-'94)	3.521	7.7132	-.2212	
	(.0690)	(.1327)	(.1241)	.96
8. India('92-'95)	-.0121	-.083	.0056	.18
	(.9543)	(.4269)	(.3760)	
9. Indonesia*('90-'95)	-.06	.154	-.01	.37
	(.7553)	(.1839)	(.1882)	
10. Jordan*	.0047	.029	-.00036	.95
	(.3847)	(.08)	(.34)	
11. Korea	-1.089	.31	-.019	.08
	(.2492)	(.4563)	(.4846)	
12. Malaysia*	.483	.1782	-.0273	.85
	(.0546)	(.4057)	(.3460)	

Country	+log of exports	+b7inflation	+b8inflation squared	R-squared
13. Mexico*('89-'95)	.001 (.7754)	.0015 (.9655)	.00059 (.4415)	.96
14. Pakistan('91-'95)	.71 (.045)	-.112 (.7252)	.0018 (.8996)	.75
15. Peru*'(93-95)	.2927 (.2986)	-.018 (.1112)	.00026 (.0654)	.22
16. Philippines	.507 (.036)	.202 (.0189)	-.0074 (.0144)	.91
17. Poland('94-'95)	-.14 (.8013)	1.53E-8 (.0002)	-5.6E-18 (.0001)	.93
18.Portugal ('89-95)	.066 (.5295)	-.013 (.8673)	.002 (.5925)	.37

* percentage changes for interest rate, exchange rate, or export rate

Country	+log of exports	+b7inflation		+b8inflation squared	R-squared
19.Sri Lanka*('93-'95)	-.106 (.5748)	.0090 (.9111)		-.0012 (.7861)	.15
20. Thailand('89-'92)	-.2 (.8396)	-.881 (.4690)		.086 (.4093)	.19
21. Turkey			Estimate of Stock Price Volatility could not be fit.		
22. Venezuela			Yule-Walker model can't be fit.		
23. Zimbabwe ('93-'95)	-		-.73 (.0639)	.0177 (.0478)	.97

The following measures were used for the short-term interest rate:

Country	short-term interest rate
1. Argentina	lending
2. Brazil	lending
3. Chile	lending
4. China	none available
5. Colombia	lending
6. Greece	working capital
7. Hungary	lending
8. India	commercial
9. Indonesia	bank
10. Jordan	discount
11. Korea	money market
12. Malaysia	money market
13. Mexico	average cost of funds
14. Pakistan	call money
15. Peru	lending
16. Philippines	treasury bill (91 days)
17.Poland	lending
18. Portugal	lending
19. Sri Lanka	interbank call loan
20. Thailand	time (3-6 month)
21. Turkey	interbank money market
22. Venezuela	commercial
23. Zimbabwe	commerical

Table 2-Results of VAR section January 1, 1989 to January 22, 1995

1. Log (stock price volatility)

* significant at the 5- or 1-percent level. (*) significant at the 10 percent level.

F-tests. Dependent Variable-Argentina

Variable	F-statistic	Significance
Argentina	704.82	.0000
Brazil	.000	.9978
Chile	6.916	.0090*
Jordan	2.156	.1433
Korea	2.849	.0926 (*)
Malaysia	.2045	.6515
Mexico	.1509	.6980
Philippines	.4142	.5204
Portugal	.8726	.3512
Venezuela	6.35	.0123*
United States	.0682	.7942

F-tests. Dependent Variable-Brazil

Variable	F-statistic	Significance
Argentina	.3051	.5812
Brazil	1613.6	.0000
Chile	1.8	.1802
Jordan	1.685	.1954
Korea	4.49	.035*
Malaysia	2.42	.1214
Mexico	.03	.858
Philippines	.7401	.3904
Portugal	.0943	.759
Venezuela	.1373	.7113
United States	.4853	.4865

F-tests. Dependent Variable-Chile

Variable	F-statistic	Significance
Argentina	.0408	.8400
Brazil	1.455	.2288
Chile	2729.8	.0000
Jordan	.6672	.4147
Korea	.9442	.3321
Malaysia	.0958	.7571
Mexico	.7296	.3938
Philippines	2.222	.1373
Portugal	.3177	.5735
Venezuela	4.475	.0354*
United States	.4013	.5270

F-tests. Dependent Variable-Jordan

Variable	F-statistic	Significance
Argentina	1.4046	.2371
Brazil	.0002	.9875
Chile	2.5062	.1146
Jordan	1504.17	.0000
Korea	.1969	.6576
Malaysia	1.7745	.1840
Mexico	1.2787	.2592
Philippines	1.5703	.2113
Portugal	.0881	.7678
Venezuela	1.970	.1617
United States	3.3982	.0664(*)

F-tests. Dependent Variable-Korea

Variable	F-statistic	Significance
Argentina	.0976	.7554
Brazil	.0936	.7680
Chile	.4656	.4956
Jordan	.5969	.4405
Korea	1.5144	.2196
Malaysia	2.114	.1482
Mexico	.3345	.5635
Philippines	.0351	.8516
Portugal	.3923	.5316
Venezuela	2.7072	.1011
United States	.2225	.6375

F-tests. Dependent Variable-Malaysia

Variable	F-statistic	Significance
Argentina	.6358	.4308
Brazil	.0017	.9672
Chile	.2884	.5917
Jordan	1.129	.2918
Korea	.4020	.5266
Malaysia	683.83	.0000
Mexico	.2944	.5879
Philippines	3.24	.0733(*)
Portugal	2.785	.0964(*)
Venezuela	.3973	.5290
United States	.0209	.8851

F-tests. Dependent Variable-Mexico

Variable	F-statistic	Significance
Argentina	.2357	.6380
Brazil	.3302	.5661
Chile	2.7470	.0986(*)
Jordan	.6909	.4100
Korea	.1402	.7083
Malaysia	1.370	.2430
Mexico	1125.07	.0000
Philippines	2.393	.1231
Portugal	.2361	.6274
Venezuela	9.700	.0021*
United States	2.831	.0937(*)

F-tests. Dependent Variable-Philippines

Variable	F-statistic	Significance
Argentina	1.1402	.2866
Brazil	.7471	.3882
Chile	2.6882	.1023
Jordan	.0298	.8630
Korea	.7733	.3800
Malaysia	3.238	.0732(*)
Mexico	.1945	.6595
Philippines	877.23	.0000
Portugal	.4773	.4903
Venezuela	.0753	.7831
United States	1.680	.1962

F-tests. Dependent Variable-Portugal

Variable	F-statistic	Significance
Argentina	.3389	.5610
Brazil	.1837	.6686
Chile	.1615	.6881
Jordan	.1995	.6555
Korea	.0002	.9874
Malaysia	2.512	.1142
Mexico	.1379	.7107
Philippines	.4882	.4854
Portugal	134.13	.0000
Venezuela	.0045	.946
United States	.6480	.4216

F-tests. Dependent Variable-Venezuela

Variable	F-statistic	Significance
Argentina	.0003	.9856
Brazil	3.651	.057*
Chile	.3307	.5663
Jordan	.3367	.5622
Korea	.9340	.3347
Malaysia	2.837	.0934(*)
Mexico	5.623	.0185*
Philippines	3.966	.0475*
Portugal	4.3821	.0373*
Venezuela	2180.63	.0000
United States	8.657	.0035*

F-tests. Dependent Variable-United States

Variable	F-statistic	Significance
Argentina	.0437	.8345
Brazil	2.2267	.1370
Chile	2.2203	.1374
Jordan	8.1263	.0047*
Korea	.5308	.4670
Malaysia	9.8428	.0019
Mexico	3.976	.0472*
Philippines	.3864	.5347
Portugal	3.625	.0580(*)
Venezuela	.4085	.5233
United States	566.52	.0000

2. Log (stock price volatility) January 1, 1989 - October 31, 1993

* significant at the 5- or 1-percent level. (*) significant at the 10 percent level.

F-tests. Dependent Variable-Colombia

Variable	F-statistic	Significance
Colombia	2715.02	.0000
Greece	.0019	.965
Thailand	.6763	.412
United States	.1416	.707

F-tests. Dependent Variable-Greece

Variable	F-statistic	Significance
Colombia	.0002	.9884
Greece	764.15	.0000
Thailand	.6423	.424
United States	1.36	.2448

F-tests. Dependent Variable-Thailand

Variable	F-statistic	Significance
Colombia	.0472	.8282
Greece	3.84	.05184*
Thailand	18.04	.0000
United States	1.705	.1934

F-tests. Dependent Variable-United States

Variable	F-statistic	Significance
Colombia	1.864	.174
Greece	2.94	.0883(*)
Thailand	.0001	.9934
United States	663.5	.0000

3. Log (stock price volatility) September 30, 1990-January 15, 1995

* significant at the 5- or 1-percent level. (*) significant at the 10 percent level.

F-tests. Dependent Variable-Indonesia

Variable	F-statistic	Significance
Indonesia	58.72	.0000
India	5.904	.0168*
Pakistan	1.558	.2150
United States	.9087	.3426

F-tests. Dependent Variable-India

Variable	F-statistic	Significance
Indonesia	2.0775	.1524
India	15.888	.00012
Pakistan	1.0006	.3194
United States	2.09	.1512

F-tests. Dependent Variable-Pakistan

Variable	F-statistic	Significance
Indonesia	3.7782	.0545(*)
India	.0752	.7845
Pakistan	156.20	.0000
United States	.0791	.7791

F-tests. Dependent Variable-United States

Variable	F-statistic	Significance
Indonesia	1.835	.1783
India	.3703	.5441
Pakistan	.9096	.3424
United States	170.59	.0000

4. Log (stock price volatility) October 3, 1993-February 26, 1995

* significant at the 5- or 1-percent level. (*) significant at the 10 percent level.

F-tests. Dependent Variable-China

Variable	F-statistic	Significance
China	.0204	.8871
Hungary	4.643	.0380*
Peru	1.287	.2641
Poland	1.324	.2574
Sri Lanka	.7944	.3787
United States	.4111	.5255
Zimbabwe	4.08	.0504*

F-tests. Dependent Variable-Hungary

Variable	F-statistic	Significance
China	1.013	.3210
Hungary	9.700	.0036
Peru	.2026	.6554
Poland	1.13	.2958
Sri Lanka	.1339	.7166
United States	.7076	.4057
Zimbabwe	3.05	.0894(*)

F-tests. Dependent Variable-Peru

Variable	F-statistic	Significance
China	2.2476	.143
Hungary	.2873	.5952
Peru	6.56	.0148
Poland	1.3044	.2609
Sri Lanka	.0839	.7737
United States	.1293	.7213
Zimbabwe	1.270	.2674

F-tests. Dependent Variable-Poland

Variable	F-statistic	Significance
China	.8596	.36003
Hungary	.0169	.8970
Peru	.1156	.736
Poland	38.830	.0000
Sri Lanka	1.080	.3066
United States	2.53	.1205
Zimbabwe	2.511	.1218

F-tests. Dependent Variable-Sri Lanka

Variable	F-statistic	Significance
China	3.23	.0807(*)
Hungary	.0050	.9441
Peru	.5444	.465
Poland	.8334	.3674
Sri Lanka	2.876	.0985
United States	.4597	.5021
Zimbabwe	.3120	.5799

F-tests. Dependent Variable-United States

Variable	F-statistic	Significance
China	2.8316	.1011
Hungary	5.933	.0199*
Peru	4.209	.0475*
Poland	.1662	.6860
Sri Lanka	1.330	.2565
United States	13.85	.0007
Zimbabwe	.7277	.3993

F-tests. Dependent Variable-Zimbabwe

Variable	F-statistic	Significance
China	6.57	.0147*
Hungary	.3311	.568
Peru	.466	.4991
Poland	.0019	.9654
Sri Lanka	.3162	.577
United States	1.98	.168
Zimbabwe	128.55	.0000

Appendix

Interpolation Using a Cubic Spline Curve

The monthly data are converted to weekly data by fitting the monthly values to a cubic spline curve. A cubic spline is a segmented function consisting of cubic polynomial functions joined together so that the whole curve and its first and second derivatives are continuous. Output values are generated from the spline approximations.

The principal justification for this interpolation procedure is that time series data have serial correlation structure in its error terms. The spline interpolation just fills in the missing values from month to weekly data in data where a trend in the data is already recognized to exist.[13]

The idea of a spline curve is the following. Draftsmen used to attach two pieces of wood together with a third piece and smooth curves were "faired" between specified points with additional strips of wood. If a curve were desired from the wood, it was formed by smoothing together two separate pieces of wood. The idea is the same as approximation. The curve

[13] Cheng Hsiao, "Identification for a Linear Dynamic Simultaneous Error-Shock Model", International Economic Review, Vol. 18, No. 1 (February 1977), 193.

that was formed of the deformed axis of the beam of wood was called an elastica.

The approximation of the curve and the additional pieces of wood that make up that approximation of the curve comprise a cubic spline curve. The spline is regarded as the draftsmen's thin beam that obeys the Bernouilli-Euler's law for the bending point of the curve. The elastica is approximated by a piecewise cubic with certain discontinuities of derivatives permitted at the junction points where two cubics join. Interpolation takes place at specified points at the junction with a minimum curvature property.

The mathematics of a cubic spline are the following. The approximations are called a mesh of points denoted as $\blacktriangle$:

$a=x_0<x<..<x_n=b$ is the interval

$$y=f(x): \qquad y_{0,}y_{1,\ldots\ldots}y_n\text{ , with index } j=1,\ldots,n\text{ ,}$$

is the function requiring interpolation. $S_{\blacktriangle}(x)$ is said to be a spline with respect to mesh $\blacktriangle$ or a spline on $\blacktriangle$. Interpolation takes place to the values y_j at the mesh locations.

Let the second derivative $f''(x)$ be continuous. For a given mesh $\blacktriangle$, let $f_j=f(x_j)$ and let $S_{\blacktriangle}(f; x)$ denote the periodic spline of interpolation to $f(x)$:

1) $S_{\blacktriangle}f\,(x) = f_j$

2) $S_\Delta f(x) = f_j$ is a cubic spline on Δ.

The following integral is formed for approximation:

$$E=\int_a^b [f''(x) - S_\Delta''(x)]^2 dx$$

where E is the approximation of S''(x) to f''(x). Evaluating the integral by expanding by the moments of the original "beam" and integrating by parts gives E of the form

$E=\int_a^b [f''(x)]^2 dx + [\text{moments}]$.

After some calculations, $E=\int_a^b [f''(x)]^2 dx+\int_a^b [S_\Delta''(x) - S_\Delta''(f;x)]^2 dx$ $-\int_a^b [S_\Delta''(f;x)]^2 dx$. The integral E is therefore a minimum for $S_\Delta''(x)=S_\Delta''(f;x)$. This property is known as the best approximation property of the spline interpolation and the foregoing discussion is its derivation. The simpler form , $\int_a^b |f''(x)|^2 dx$, is often a good approximation to the integral of the square of the curvature for a curve y=f(x). This integral is routinely called the minimum curvature property.

The effectiveness of the spline curve in approximation can be explained to a considerable extent by its convergence properties. If $f^q(x)$ is continuous on interval [a,b] (q=0,1,2,3,or 4) $S_\Delta''(f; x)$ is found to converge to f(x) on a sequence of meshes at least as rapidly as the approach to zero of the qth power. The approach to zero of the qth power is the mesh norm $\|\Delta\|=\max_j h_j$

with $h_j = x_j - x_{j-1}$. In some cases it is required that the ratio of maximum interval length to minimum interval length in the respective meshes be bounded. In many cases it is only required that the limit of the mesh norm be zero. That limit ensures convergence which allows the desired interpolation of missing values when converting monthly to weekly data.

The existence of a spline curve is proven through these convergence properties. If $\{\blacktriangle k\}$ is a sequence of meshes on [a,b] with S-hat$_{\blacktriangle k}$ (x) $\|\blacktriangle k\| \to 0$ as $k \to \infty$, then S-hat$_{\blacktriangle k}$ (x) can be a spline interpolating to f(x) at the points $\blacktriangle k$ with derivative 0. The sequence {S-hat$_{\blacktriangle k}$ (x)} converges uniformly to f(x) on [a,b]. If f-hat(x) is assumed to be continuous on [a,b], then the spline and its derivative converge.

In summary, if there is a mesh $\blacktriangle$: $a=x_0<x<..<x_n=b$ and a set of real numbers

$y=f(x)$: $y_0.y_1.......y_n$, of all the functions f(x), the spline function $S_\blacktriangle''(f;a)=S_\blacktriangle''(f;b)=0$. This property leads to minimizing the integral $\int_a^b|f''(x)|^2dx$. The calculations are described above.

Curve fitting has recommended methods but no exact procedure. It is recommended to use as close to uniform distributions of mesh points as possible. Care must also be taken that the curves being fitted actually possess the continuity conditions required. These conditions are satisfied in the interpolation of this data. For constants a,b, and c, the cubic polynomial functions take the form of $f(x) = ax + bx^2 + cx^3$ and the spline function takes the form of $S(ax + bx^2 + cx^3)$.

In this way, monthly data can be converted to weekly data. The software fits meshes and then integrates over a spline function for an approximation of weekly data. Outliers result when negative values to fit the cubic shape of the spline curve; they are outliers when they are produced for variables where the raw data has no negative values. As a result, missing values in the stock price indices were left. An attempt to interpolate the missing values produced outliers to the data that distorted the results of estimation. Outliers were not produced in the same way for the other variables.

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