The Spline GARCH Model for Unconditional Volatility and its Global Macroeconomic Causes

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Abstract

We introduce a new model to measure unconditional volatility, the Spline-GARCH. The model is applied to equity markets for 50 countries for up to 50 years of daily data. Macroeconomic determinants of unconditional volatility are investigated. It is found that volatility in macroeconomic factors such as gdp growth, inflation and short term interest rates are important explanatory variables that increase volatility. There is evidence that high inflation and low growth of output are positive determinants. Volatility is higher for emerging markets and for markets with small numbers of listings but also for large economies.

1. Introduction

Modeling financial market volatility has held the attention of scholars and financial practitioners for more than two decades. We now know a great deal about the stochastic process of volatility in many developed markets and its applications to financial and economic decisions such as portfolio allocation, risk management and asset pricing. However we know relatively little about the causes or determinants of financial volatility, particularly at low frequencies. This paper introduces a new model for unconditional volatility, the Spline-GARCH, and investigates the relation between it and a variety of macroeconomic variables in a global context.

Different causal explanations of financial volatility have been offered from different perspectives. For example, Black (1976) and Christie (1982) attribute return volatility (at the firm level) to financial leverage, Mehra and Sah (2002) explain changes in volatility through changes in discount factors and attitudes towards risk, Grossman (1989) points out the role of financial innovation, and David and Veronesi (2004) argue that uncertainty about future values of fundamentals is a key factor driving volatility.

At a more basic level, the primitive elements creating volatility are linked to the price formation process. Indeed, price changes and volatility are generated by the arrival of new information. Volatility clustering takes place either when this information arrives in clusters, or when the information content of news is not uniformly assessed by the investors, creating a period of price discovery. Therefore, the information content of the news and the nature of the news arrival process are primary causes of market volatility in the short run. A number of studies have analyzed this causal relation in the short run, for example Clark (1973), and Andersen (1996). However, little is known about the long run causal relation. For instance, a general assumption in the literature is that volatility reverts to its unconditional mean; therefore, a natural question is, what determines this unconditional mean? Even though the question seems basic, there is no work about the determinants of unconditional volatility. This paper fills this gap by introducing a new model for unconditional volatility under a semi-parametric GARCH framework. In fact, we introduce the Spline-GARCH model that keeps the attractive properties of the GARCH(1,1) model for the short run volatility dynamics, and introduces a new component that non-parametrically estimates the unconditional volatility (or long run volatility).

We use evidence from international markets to empirically study the determinants of unconditional volatility. Taking a sample of stock markets corresponding to different countries, we relate their unconditional volatilities to macroeconomic determinants suggested by theory, and previous empirical studies on conditional volatilities. We also motivate the cross-sectional analysis based on the time series features of the variables, such as the correlation structure in the data. This leads us to a Seemingly Unrelated Regressions (SUR) framework that efficiently captures the observed correlation in the disturbances. We check for the robustness in our estimates by using alternative measures of long run volatilities, such as realized volatility over a long horizon.

This paper is organized as follows: First, we introduce the Spline-GARCH model for unconditional volatility. Next, we present a description of the data followed by a discussion on the definition and construction of the variables involved in the cross-sectional analysis. Then, we motivate the econometric approach for the cross-sectional analysis and discuss the estimation results of the determinants of long run volatilities. Next, we present a robustness section with estimation of alternative models using other proxies for unconditional volatilities. Lastly, we provide concluding remarks.

2. A New Time Series Model for Conditional and Unconditional Volatility

Our time series model extends the GARCH(1,1) model introduced (in a generalized form) by Bollerslev (1986) offering a more flexible specification of unconditional volatility using a semi-parametric framework. Despite the success of the standard GARCH(1,1) model in describing the dynamics of conditional volatility in financial markets (particularly in the short run), its implications for long run volatilities are restrictive, in the sense that this model implies a constant expected volatility in the long run (i.e., the long run volatility forecast is constant). This feature does not seem to be consistent with the time series behavior of realized (and implied) volatilities of stock market returns (see figure #). Consequently, we need a model flexible enough to generate an expected volatility that captures the long run patterns observed in the data. To accomplish this goal, we modify the standard GARCH(1,1) model by introducing a trend in the volatility process of returns. Specifically, this trend is modeled non-parametrically using an exponential quadratic spline, which generates a smooth curve describing the long run volatility component based exclusively on data evidence. Our Spline-GARCH model for stock returns can be expressed as follows:

(1) $$r_t = \mu + \sqrt{\tau_t g_t}\varepsilon_t, \text{ where } \varepsilon_t \mid \Phi_{t-1} \sim N(0,1)$$

(2) $$g_t = (1-\alpha-\beta) + \alpha\left(\frac{(r_{t-1}-\mu)^2}{\tau_{t-1}}\right) + \beta g_{t-1}$$

(3) $$\tau_t = c\exp\left(w_0 t + \sum_{i=1}^{k} w_i\left((t-t_{i-1})_+\right)^2 + z_t\gamma\right)$$

where,

Φ_t denotes the information set including the history of returns up to time *t* and weakly exogenous or deterministic variables z_t,

$$(t-t_i)_+ = \begin{cases} (t-t_i) & \text{if } t > t_i \\ 0 & \text{otherwise} \end{cases}$$

and $\{t_0 = 0, t_1, t_2, ..., t_k = T\}$ denotes a partition of the time horizon *T* in *k* equally-spaced intervals.

$\Theta = \{\mu, \alpha, \beta, c, w_0, w_1, ..., w_k\}$ includes the parameters estimated in the model. Since *k*, the number of knots in the spline model, is given exogenously, we can use an information criterion to determine an "optimal" choice for this number, which in fact governs the cyclical pattern in the long run trend of volatility. Large values of *k* imply more frequent cycles. The "sharpness" of each cycle is governed by the w_i's coefficients. Notice that the normalization of the constant term in the GARCH equation implies that the unconditional volatility depends exclusively on the coefficients of the exponential spline. In fact, the unconditional volatility is:

(4) $$E\left[(r_t-\mu)^2\right] = \tau_t E(g_t) = \tau_t$$

Our semi-parametric approach has the potential to capture both short and long term dynamic behavior of market volatility. Equation (2) characterizes the short term dynamics keeping the nice properties of GARCH models in fitting and forecasting volatility processes at high and low frequencies[1]. Equation (3) describes, non-parametrically, the long term dynamics of volatility with a smooth differentiable curve

[1] See Andersen and Bollerslev (1998).

including *k-1* inflexion points that (naturally) capture cyclical patterns. Figure (1) illustrates the model for the US, based on the S&P500. The graph shows how the Spline-GARCH model fits short and long run patterns of volatility during the period 1955-2003. The long run trend suggested by the data observes a cyclical behavior that may be associated with the business cycle. In addition, the graph shows that the assumption suggesting that volatility reverts towards a constant is not appealing to describe long run volatility behavior. In figure 2, similar pictures are presented for another six countries. In the following sections, we use evidence of international markets to explore the determinants of the expected volatility presented in equation (4).

3. Data Sources

Our empirical analysis considers stock market returns, stock exchange features, and macroeconomic variables from different economies. Using the index associated with the main stock exchange, we collect daily data of several countries on stock market returns from Datastream and Global Financial Data. Our sample includes all developed countries and most emerging markets that experienced significant liberalization during the 1980's and 1990's, as described in Bekaert and Harvey (2000).

We also collect information for different years on the size and diversification of each market, such as market capitalization and the number of listed companies. The former is obtained from Global Financial Data and the official web pages of the exchanges. The sources for the latter are: the World Federation of Exchanges, the Ibero-American Federation of Exchanges (FIAB), and official web pages of the exchanges.

The sources for our macroeconomic variables are Global Insight/WRDS, Global Financial Data, and the Penn World Tables. These variables include: GDP, inflation indices (Consumer Price Indices are used to measure inflation), exchange rates, and short term interest rates. The set of countries with available macroeconomic data is smaller than the set with available financial time series data. Thus, we are left with a reduced sample of 48 countries. Table (1) lists these countries, the names of the exchanges and market indices, their IFC country classification as developed or emerging markets, as well as general exchange features, such as average values for the number of listed companies and market capitalization.

3.1 Variables Discussion

We start with a description of the dependent variable. In this regard, given that volatilities are not directly observed, we need to define a measure of long run volatilities to construct our dependent variable.[2] For each country, we use the Spline-GARCH model introduced in section (2) to fit its daily time series of market returns. We use the BIC to

[2] Andersen et. al (2003) argue that under suitable conditions, realized volatilities can be thought as the observed realizations of volatility. We present estimation results for this alternative measure of long term volatilities in section (5).

select the optimal number of knots associated with the spline component. In each case, we obtain the unconditional expected volatility described in equation (4). Thus, a measure of the unconditional volatility can be defined as the average of the unconditional volatilities over a long term horizon, namely one year. It is important to mention that we tried to maximize the number of daily observations used in the estimation for each country; however, either data availability constrains or age of the exchanges lead to different sample windows.

We appeal to economic theory and previous empirical evidence to select the potential determinants of long run volatilities. Levels as well as fluctuations of fundamental variables are the natural candidates. Previous research has pointed out the relation between volatilities and the business cycle; for example, Schwert (1989) and Hamilton and Lee (1996) find economic recessions as the most important factor influencing the US stock return volatility. We consider the growth rate of real GDP as a variable accounting for changes in real economic activity.

Volatility and uncertainty about fundamentals are also potential factors affecting market volatility. For example, Gennotte and Marsh (1993) derive returns volatility and risk premia based on stochastic volatility models of fundamentals; David and Veronesi (2004) identify inflation and earnings uncertainty as sources of stock market volatility and persistence. We consider measures of macroeconomic volatility to account for this uncertainty. Specifically, we construct a proxy for inflation volatility based on our CPI quarterly time series. We obtain the absolute values of the residuals from an AR(1) model, and then we compute their yearly average.

$$\Delta \log\left(y_t\right) = c + u_t, \quad u_t = \rho u_{t-1} + e_t$$

$$\sigma_{y,t}^2 = \frac{1}{4} \sum_{j=t-2}^{t+1} \left|e_j\right|$$

Following the same setup, we construct other proxies for country economic uncertainty linked to fundamentals. In particular, we estimate volatilities of real GDP, interest rates (without logs) and exchange rates based on the residuals of fitted autoregressive models. Exchange rates are measured as US$ per unit, and interest rates are based on short term government bonds.

Some country-based empirical studies have suggested that market development is an important element in explaining differences in market volatilities across countries. For example, De Santis and Imrohoroglu (1997) find higher conditional volatilities, as well as larger probabilities of extreme events, in emerging markets relative to developed markets. Moreover; Bekaert and Harvey (1997) find that market liberalizations increase the correlation between the local market and the world market, but they do not find significant effects on market volatilities. In order to capture the effect of market development in our analysis we construct two dummy variables for emerging markets and transition economies. The emerging market classification comes from the IFC; we define transition economies as the former socialist economies, such as the Central European and Baltic countries in our sample.

To explain further variations in the cross-sectional stock market volatilities it is important to account for other factors associated with market liberalizations, for example macroeconomic reforms relevant for both increasing efficiency in risk sharing and increasing market liquidity. In emerging economies many macroeconomic reforms are intended to open the economies to international trade and to improve institutional control of inflation. Bekaert, Harvey, and Lundblad (2004) find that a larger external sector, as well as a larger inflation rate, is positively related to consumption and GDP growth volatility. Since we are interested in variables explaining volatility of fundamentals, we account for the size of each country external sector and inflation rates. Specifically, we measure the external sector as the sum of imports and exports divided by real GDP (i.e., total trade as a percentage of GDP). In addition, we measure inflation rates as the growth rate of the CPI.

Cross-sectional variation in market volatilities may also be related to the size of the markets. We would expect that larger markets have advantages in terms of offering broader diversification opportunities and probably lower trading costs. We consider two different variables to account for the market size. The first one is the log of the annual market capitalization of each exchange. The second one is the log of nominal GDP in US dollars. Having these variables in logs allows for testing the effect of the stock market size as a proportion of the overall value of the economy (ratio market capitalization-GDP). This ratio can be used as a measure of how developed is the stock market and as a proxy for the degree of integration in terms of foreign investment.[3] All of these variables are converted to US dollars using annual exchange rates. Finally, we consider the number of listed companies on each exchange as a variable proxying the market size and the span of market diversification opportunities. Table (2) summarizes the variables of our analysis.

4. Cross-Sectional Analysis of Unconditional Volatilities

In this section, we describe our cross-sectional analysis of expected market volatilities in the long run. Before describing the general setup, it is important to point out some data issues and conventions. First, we relate long run periods with annual intervals.[4] Thus, for each of the variables introduced above, we construct annual averages. Next, for each country, we have to match the annual long run volatility time series with several macroeconomic time series. This process leads country-specific sample windows, and therefore to an unbalanced panel of countries. Moreover, the number of countries increases with time, since recent data is available for most of the countries, and also because many markets started operations during the 1990's (e.g. transition economies). Therefore, in order to keep a relatively large number of countries in the cross-sectional dimension, we consider a panel that covers from 1990-2003. This data structure can be

[3] Bekaert and Harvey (1997) consider the ratio market capitalization to GDP and the size of the trade sector as measures of the country's degree of financial and economic integration that affect the inter-temporal relation between domestic market volatilities and world factors.

[4] This convention has no effect in our framework. We could have taken a different horizon and followed the same process.

summarized in a system of linear equations projecting, for each year, the unconditional volatility on the explanatory variables described in table (2),

$$Uvol_{i,t} = x'_{i,t}\beta_t + u_{i,t},\ t = 1,2,...,T,\ i = 1,2,...,N_t \tag{5}$$

where $x_{i,t}$ is a $k \times 1$ vector of explanatory variables, and $u_{i,t}$ is the error term assumed to be contemporaneously uncorrelated with $x_{i,t}$.[5]

The next task is to find an econometric approach that efficiently accounts for the features observed in the structure of our data. We start by looking at the correlation structure of the data across time. In particular, we select a sub-panel from 1997-2003 to have an almost balanced structure. We look at the correlation across years of long run volatilities, regressors, and residuals coming from individual regressions for each year. Tables (3) and (4) present the correlation across time of uconditional volatilities and residuals, respectively. These tables show high correlation of the residuals, suggesting that unobservable factors affecting expected volatilities are likely to be serially correlated across time. In addition, even higher correlation is observed on the dependent variable suggesting little variation across time. Similarly, it is observed that many of the explanatory variables are also highly correlated across time, showing again little time variability. Some exceptions that show lower correlation across time are the real GDP growth rate and the exchange rate volatility.

The observation of these features motivates our econometric approach. As usual in cross sectional studies, we assume that the errors are uncorrelated in the cross-section. However there is clear autocorrelation. A method that efficiently handles autocorrelation in the unobserved errors is appealing. The Seemingly Unrelated Regressions (SUR) model developed by Zellner (1962) provides a framework that imposes no assumptions on the correlation structure of the errors and easily incorporates restrictions on the coefficients. The presence of large autocorrelations across the disturbances, as suggested in table (4), implies important gains in efficiency from using FGLS in a SUR system as well as improved standard errors. Alternative panel data approaches that impose further restrictions could be considered; however, their underlying assumptions and estimation features seem to be less attractive based on the features of our data. For example, the low variation over time observed in many of the explanatory variables indicates that fixed effects models can lead to imprecise estimates (see Wooldridge, 2002). On the other hand, even though random effects models allow for some time correlation, the structure of the covariances is restrictive in the sense that it comes exclusively from the variance of the individual effects, which is assumed to be constant across time. This feature does not seem appealing based on the evidence in table (2). In addition, random effects models assume exogeneity of the individual (or time)

[5] The assumption $E(x'_{i,t}u_{i,t}) = 0,\ t = 1,2,...,T,\ i = 1,2,...,N_t$ does not rule out non contemporaneous correlation; so, the error term at time t may be correlated with the regressors at time t+1. Therefore, in this setup financial volatility can cause macroeconomic volatility, as it is suggested in Schwert (1989). However when SUR estimation is used, the assumption of exogeneity will be maintained

effects, which raises additional misspecification issues. Therefore, the SUR method imposes less restrictions allowing for time fixed effects and flexible autocorrelation structure. In addition, we assume that the coefficients remain constant over time with a time specific intercept. This is a testable restriction on the general SUR setup.

Using this SUR modeling strategy, we start our cross sectional analysis by exploring the relationship between unconditional volatilities and each of the explanatory variables, one at a time. Table (5) presents the estimation results of the system of cross sectional regressions on single explanatory variables.[6] From this preliminary analysis, we observe positive relations among long term market volatilities and each of the following variables: emerging markets, inflation growth, and macroeconomic volatilities (associated with interest rates, exchange rates, GDP, and inflation). In contrast, the following variables show a negative relation with long run market volatility: transition economies, growth rate of GDP as well as market size variables, such as log market capitalization, log nominal GDP, and number of listed companies. The results are significant for most variables except for transition economies and log nominal GDP in current US dollars.

Next, we estimate the full system of equations described in (5), which includes all the explanatory variables. The corresponding results are presented in the first column of table (6). From this analysis, we observe that emerging markets show larger expected volatility compared to developed markets. The effect is significant and consistent with the empirical evidence about volatility of emerging markets (see Bekaert and Harvey, 1997). It is however much smaller than in the univariate regressions. Transition economies have only slightly larger volatility than developed economies. Market size variables show different results. Whereas log market capitalization has a not significant negative effect, log nominal GDP in current US dollars is positive and significant. The positive effect dominates, suggesting that larger market sizes are associated with larger expected volatilities. In contrast, the number of listed companies in the exchange has a negative effect on volatility. This suggests that markets with more listed companies may offer more diversification opportunities, reducing the overall expected volatility.

In regard to real economic activity variables, the results show that economic recessions increase unconditional volatility, and inflation growth also affects it positively. These results indicate that countries experiencing low or negative economic growth observe larger expected volatilities than countries with superior economic growth. Similarly, countries with high inflation rates experience larger expected volatilities than those with more stable prices. Although the effect is not significant for GDP growth, the effect is larger and highly significant for inflation rates.

In relation to volatility of macroeconomic fundamentals, the results suggest that volatility of inflation, as well as volatility of GDP, are strong determinants of unconditional market volatility. Both variables are associated with significant positive effects. The coefficient on interest rate volatility is also positive and significant but small in magnitude. The effect of exchange rate volatility is negative, but small and quite insignificant. This

[6] The constant term is allowed to vary across years.

evidence encourages theoretical work relating volatility of fundamentals to causes of fluctuations in unconditional market volatility.

We also consider plausible dimension reductions based on the significance of the explanatory variables. In columns 2 to 5, we present different model specifications based on a reduction process that drops the least significant variable one at a time. For example, the least significant variable in model M1 is volatility of the exchange rate. Thus, dropping this variable leads to specification M2. Similarly, the least significant variable in M2 is log market capitalization, which is omitted in specification M3, and so on. In this process, the goodness of fit in each model is given by the concentrated likelihood, and therefore by the determinant of the residual covariance. In addition, to select an optimal reduction, we take an information criterion approach; in particular, we select a BIC type of penalization for increasing the number of parameters. The last row of table (6) suggests that the BIC favors specification M4, for which the indicator of transition economies, log market capitalization, and volatility of exchange rates are omitted. Therefore, the reduction process leads to a model with eight explanatory variables.

The last two columns of table (6) correspond to a reduction based on dropping the least significant variables from individual regressions, as presented in table (5). In this case, the least significant variable is log nominal GDP in current dollars, which is dropped from specification M6 in table (6). The other variable that is not individually significant is the indicator of transition. Both variables are dropped in specification M7. In this alternative reduction process, the BIC favors model specification M6.

5. Robustness

In this section, we compare the estimation results of the cross-sectional expected volatility model with alternative measures of long term volatilities. First, we estimate a system of equations using the annual realized volatility instead of the Spline-GARCH unconditional volatility. This leads the following system:

$$(6) \qquad realized\_volatility_{i,t} = x'_{i,t}\,\beta_t + v_{i,t}, \; t = 1,2,...,T, \; i = 1,2,...,N_t$$

where the same explanatory variables are included, and $v_{i,t}$ satisfies the same conditions mentioned above. The estimation results for realized volatilities are presented in table (7). We observe the same signs for most of the variables with exception of volatility of exchange rate, and volatility of inflation. Specifically, volatility of exchanges rate shows a positive effect on annual realized volatilities, contrasting with the previous case, in which the effect was small and negative; however, in both cases, the effect of this variable is not significant. In addition, the volatility of inflation observes a negative and insignificant effect on realized volatilities, which also contrast with the high significant positive effect on expected volatilities found in the Spline-GARCH model.

Columns 2-4 of table (7) show estimation results for successive reductions based on the same criterion described above. For realized volatilities, the least significant variable is the indicator of transition, followed by volatility of inflation, and inflation growth. In this case, our information criterion suggests that omitting these three variables is optimal. Hence, in contrast with the unconditional volatility from the Spline-GARCH model, the realized volatility shows almost no responsiveness to inflation variables but is significantly negatively affected by the market capitalization. These results may be due to the fact that annual realized volatility is a noisier measure of long term volatility.

We also compare the results in levels from the previous section with the results from a model in logs. Specifically, we estimate a system of equations, in which the log of the unconditional volatility from the Spline-model is the dependent variable for each year. Table (8) presents estimation results for this case. Note that for most of the variables the signs do not change with respect to the model in levels. The only exception is the GDP growth rate, whose coefficient turns positive, albeit it is the least significant variable. In fact, our reduction process suggests that omitting only this variable leads to the “best” specification. Moreover, the alternative reduction process that focuses on the statistical significance from individual regression systems, suggests a model in which only the log of nominal GDP in current dollars is omitted (see table (8), column 6). In such case, the GDP growth variable maintains its negative sign.

6. Concluding Remarks

We introduce a new model to characterize the long run pattern of market volatility in terms of its unconditional expectation. Keeping the attractiveness of a GARCH framework, we model the long run trend of volatility taking a non-parametric approach that leads to a smooth curve that describes the unconditional volatility.

After proposing a method to estimate the long term volatility component, a deeper question arises: what causes this unconditional volatility? We answer this question empirically. We perform a cross-sectional analysis of unconditional volatility to explore its macroeconomic determinants by considering evidence from international markets.

Our empirical evidence suggests that long term volatility of macroeconomic fundamentals, such as inflation and GDP, are primary causes of unconditional market volatility. These variables show a strong positive effect in the cross sectional analysis. In addition, volatility of short term interest rates also presents a positive effect, but in this case, the impact is small.

In line with other empirical studies, we find that market development is also a significant determinant. Emerging markets show higher levels of unconditional market volatilities. An explanation may be that emerging markets are typically associated with larger inflation rates. Our results show that the larger the long term inflation rate, the larger the unconditional market volatility.

Market size variables are also important. The number of listed companies, as an indicator of the span of local diversification opportunities, negatively affects unconditional market volatility.

We compare our results with the results of annual realized volatility as an alternative measure of unconditional volatility. We find changes in significance due to the fact that realized volatility is a noisier measure of unconditional volatility. Inflation variables are no longer good predictors of annual realized volatilities.

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Figure 1

Conditional and Unconditional Volatility S&P500

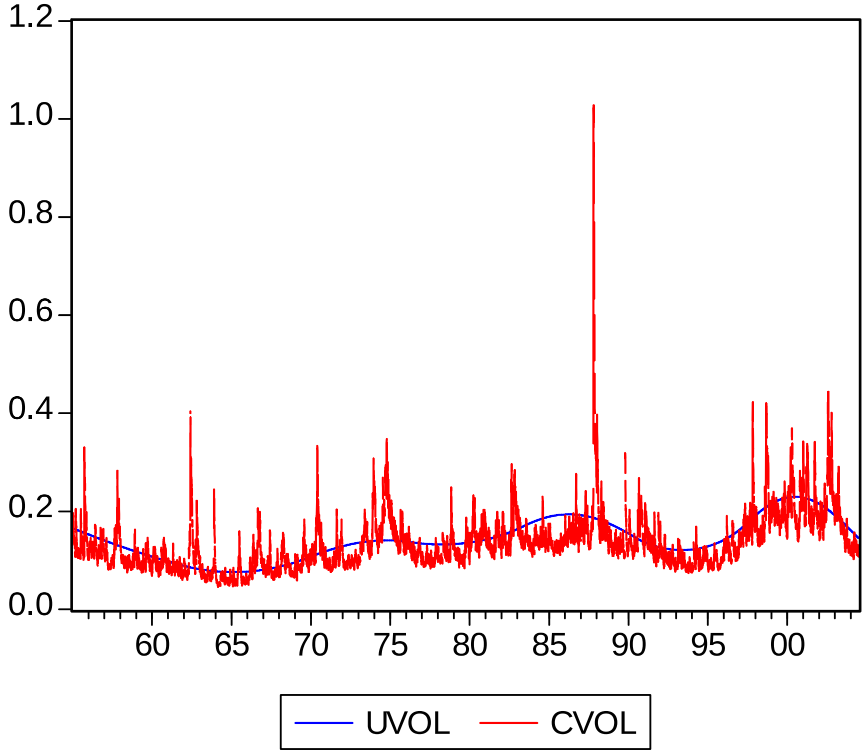
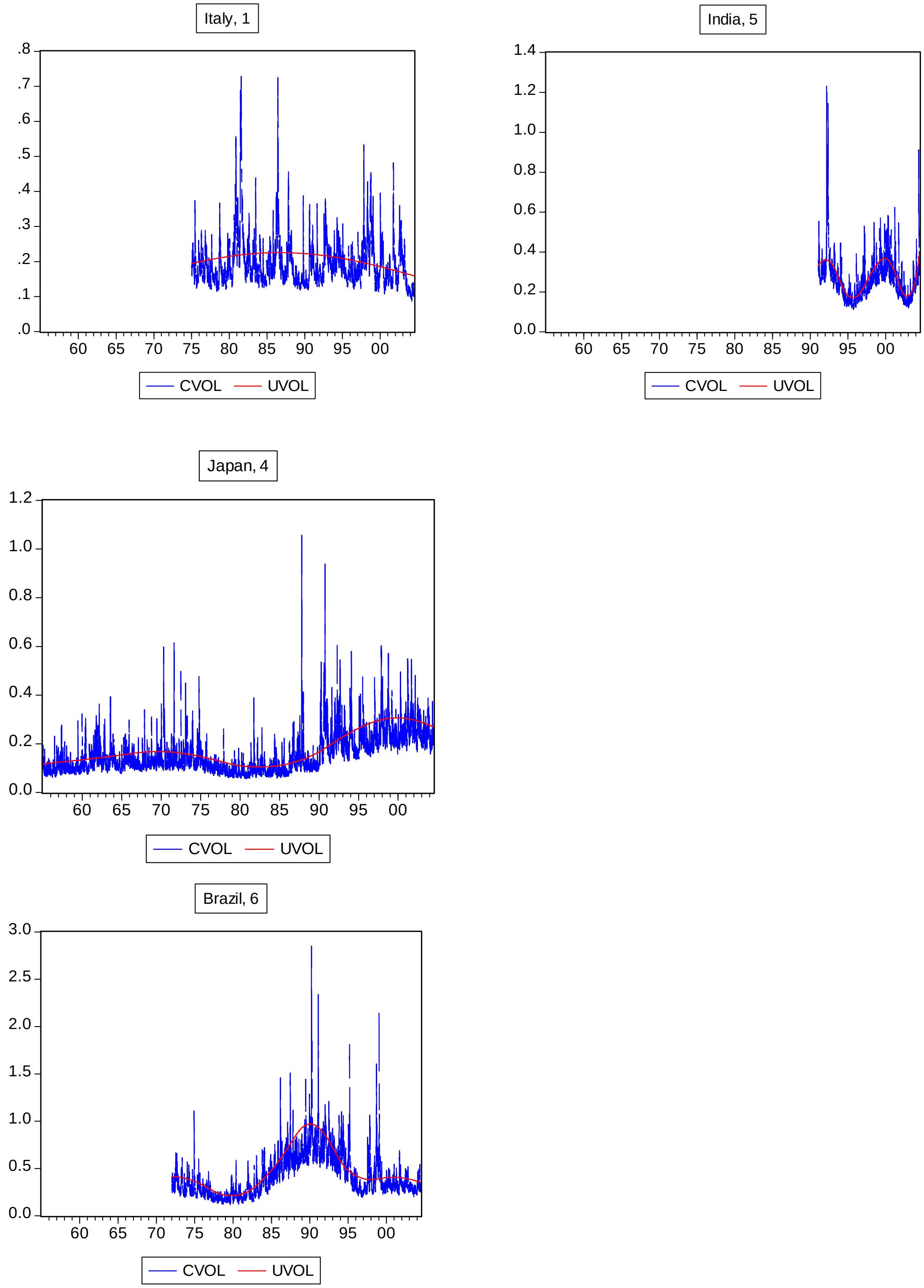
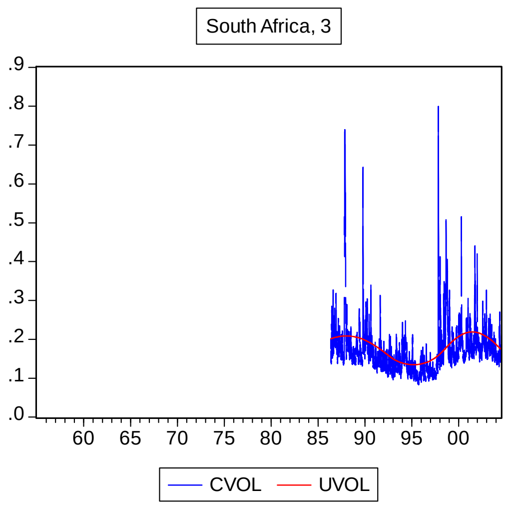


Figure 2
Conditional and Unconditional Volatilities of Selected Countries




South Africa, 3
.9
.8
.7
.6
.5
.4
.3
.2
.1
.0
60
65
70
75
80
85
90
95
00
CVOL
UVOL

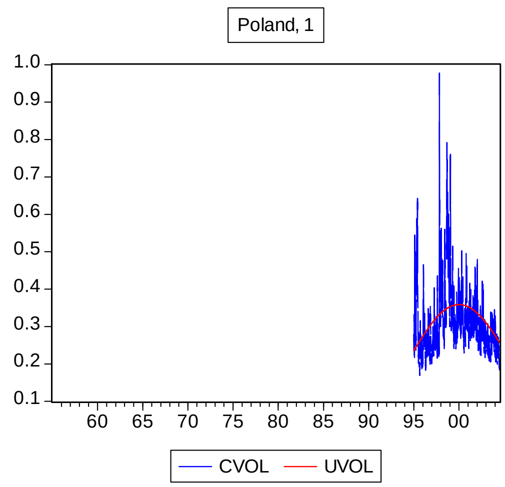

Poland, 1
1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
60
65
70
75
80
85
90
95
00
CVOL
UVOL

Table (1)

Country	Market Clasification	Exchange	Name of the Index	Average No. of Listings	Average Market Capitalization
Argentina	emerging	Buenos Aires	IVBNG	143	35352.96
Australia	developed	Australian	ASX	1236	295354.2
Austria	developed	Wiener Börse	ATX	137	31104.35
Belgium	developed	Euronext	CBB	1229	128803.2
Brazil	emerging	Sao Paulo	BOVESPA	513	155037
Canada	developed	TSX Group	S&P/TXS 300	1633	501122.3
Chile	emerging	Santiago	IGPAD	261	54529.27
China	emerging	Shanghai Stock Exchange	SSE-180	370	216199.3
Colombia	emerging	Bogota	IGBC	109	11480.09
Croatia	emerging	Zagreb	CROBEX	57	2406
Czech Republic	emerging	PSE	SE PX-50 Index	563	13319.22
Denmark	developed	Copenhagen	KAX All-Share Index	241	72720.3
Ecuador	emerging	Guayaquil	Bolsa de Valores de Guayaquil Index	34	1746.738
Finland	developed	Helsinki	HEX	106	113409
France	developed	Euronext	CAC-40*	1229	752041.9
Germany	developed	Deutsche Börse	DAX	880	759628.3
Greece	developed	Athens	Athens SE General Index	224	56050.52
Honk Kong	developed	Hong Kong	Hang Seng Composite Index	637	389810
Hungary	emerging	Budapest	Budapest SE Index*	53	9728.453
India	emerging	Mumbai	Mumbay SE-200 Index	5696	128732.4
Indonesia	emerging	Jakarta	Jakarta SE Composite Index	243	36744.79
Ireland	developed	Irish	ISEQ Overall Price Index	89	69934.38
Israel	emerging	Tel-Aviv	TA SE All-Security Index	563	41720.75
Italy	developed	Borsa Italiana	Milan MIB General Index	263	374715.4
Japan	developed	Tokyo	Nikkei 225	1911	2930639
Korea	emerging	Korea	KOSPI	708	163264.7
Lithuania	emerging	National SE of Lithuania	Lithuania Litin-G Stock Index	174	3190.185
Malaysia	emerging	Bursa Malaysia	KLSE Composite	610	141464.6
Mexico	emerging	Mexico	IPC	208	119904.7
Netherlands	developed	Euronext	AEX	1229	366983.1
New Zealand	developed	New Zealand	New Zealand SE All-Share Capital Index	190	23119.93
Norway	developed	Oslo	Oslo SE All-Share Index	175	50232.67
Peru	emerging	Lima	Lima SE General Index	235	8892.879
Philippines	emerging	Philippine	Manila SE Composite Index	205	33072.59
Poland	emerging	Warsaw	Poland SE Index (Zloty)	129	15687.93
Portugal	developed	Euronext	Portugal PSI General Index*	1229	32279.57
Russia	emerging	Russian Exchange	Russia AKM Composite	169	52182.45
Singapore	developed	Singapore	SES All-Share Index	336	114633.9
Slovak Republic	emerging	Bratislava	SAX Index	764	3909.196
South Africa	emerging	JSE South Africa	FTSE/JSE All-Share Index	618	200916.7
Spain	developed	Spanish Exchanges (BME)	Madrid SE General Index	3119	315363.5
Sweden	developed	Stockholmsbörsen	SAX All-Share index	242	206177.8
Switzerland	developed	Swiss Exchange	Switzerland Price Index	431	463321.4
Taiwan	emerging	Taiwan	Taiwan SE Capitalization Weighted Index	410	237885.5
Thailand	emerging	Thailand	SET General Index	369	68325.18
Turkey	emerging	Istanbul	Istanbul SE IMKB-100 Price Index	227	41548.86
United Kingdom	developed	London	FTSE-250*	2497	1739880
United States	developed	NYSE	S&P500	2298	6805999
Venezuela	emerging	Caracas	Caracas SE General Index	71	7718.482

Source: Global Financial Data and Datastream*
Yearly Averages over the period 1990-2003
Units market capitalization: USD millions

Table (2)

Explanatory Variables	
Name	**Description**
emerging	Indicator of Market Development (1=Emerging, 0=Developed)
Transition	Indicator of Transition Economies (Central European and Baltic Countries)
log(mc)	log Market Capitalization ($US)
log(gdp_dll)	Log Nominal GDP in Current $US
nlc	Number of Listed Companies in the Exchange
grgdp	GDP Growth Rate
gcpi	Inflation Growth Rate
vol_irate	Volatility of Short Term Interest Rate*
vol_forex	Volatility of Exchange Rates*
vol_grgdp	Volatility of GDP*
vol_gcpi	Volatility of Inflation*

*Volatilities are obtained from the residuals of AR(1) models

Table (3)

Correlation Long-Run Volatilities Across Years

	VOLLONG1997	VOLLONG1998	VOLLONG1999	VOLLONG2000	VOLLONG2001	VOLLONG2002	VOLLONG2003
VOLLONG1997	1	0.820560553	0.754137046	0.724828446	0.667415013	0.642714735	0.777764794
VOLLONG1998	0.820560553	1	0.84041443	0.674195939	0.498183331	0.469030306	0.572699325
VOLLONG1999	0.754137046	0.84041443	1	0.887897418	0.735096081	0.712585703	0.704775087
VOLLONG2000	0.724828446	0.674195939	0.887897418	1	0.939840931	0.891587138	0.845811705
VOLLONG2001	0.667415013	0.498183331	0.735096081	0.939840931	1	0.948595077	0.880436163
VOLLONG2002	0.642714735	0.469030306	0.712585703	0.891587138	0.948595077	1	0.916503359
VOLLONG2003	0.777764794	0.572699325	0.704775087	0.845811705	0.880436163	0.916503359	1

Table (4)

Correlation of Residuals from Yearly Regressions (1997-2003)

	RES97	RES98	RES99	RES00	RES01	RES02	RES03
RES97	1	0.66318767	0.601674796	0.639815059	0.559989104	0.580367021	0.679975201
RES98	0.66318767	1	0.760534138	0.694087741	0.445010779	0.384607563	0.443721789
RES99	0.601674796	0.760534138	1	0.775342395	0.494990969	0.5159987	0.484421172
RES00	0.639815059	0.694087741	0.775342395	1	0.862771307	0.751095114	0.748196165
RES01	0.559989104	0.445010779	0.494990969	0.862771307	1	0.885393806	0.848247418
RES02	0.580367021	0.384607563	0.5159987	0.751095114	0.885393806	1	0.888086516
RES03	0.679975201	0.443721789	0.484421172	0.748196165	0.848247418	0.888086516	1

Table (5)

Individual SUR Regressions

	Coefficient	Std. Error	t-Statistic	Prob.	Det residual covariance
emerging	0.0853	0.0187	4.5588	0.0000	2.74E-38
Transition	-0.0146	0.0184	-0.7927	0.4282	5.52E-38
log(mc)	-0.0092	0.0032	-2.8495	0.0045	1.37E-37
log(gdp_dll)	-0.0034	0.0052	-0.6626	0.5078	9.68E-37
log(mc/gdp_dll)	-0.0274	0.0050	-5.5075	0.0000	1.65E-36
nlc	0.0000	0.0000	-2.4753	0.0136	4.76E-37
grgdp	-0.7150	0.1350	-5.2965	0.0000	1.46E-37
gcpi	0.5631	0.0446	12.6113	0.0000	8.13E-38
vol_irate	0.0085	0.0006	14.1663	0.0000	4.80E-38
vol_forex	0.5644	0.0434	13.0083	0.0000	7.24E-38
vol_grgdp	1.0974	0.1097	10.0080	0.0000	4.04E-38
vol_gcpi	0.9115	0.0895	10.1836	0.0000	1.03E-37

Table (6)

Estimation Results: SUR Models for Long Run Volatilities

	M1	M2	M3	M4	M5	M6	M7
emerging	0.0307	0.0312	0.0351	0.0350	0.0309	0.0297	0.0269
	(0.0147) **	(0.0146) **	(0.0138) **	(0.0136) **	(0.0130) **	(0.0147) **	(0.0144) *
transition	-0.0187	-0.0187	-0.0195	-0.0184		-0.0163	
	(0.0184)	(0.0184)	(0.0181)	(0.0178)		(0.0183)	
log(mc)	-0.0036	-0.0037				0.0079	0.0092
	(0.0062)	(0.0062)				(0.0043) *	(0.0040) **
log(gdpus)	0.0198	0.0201	0.0167	0.0170	0.0182		
	(0.0077) **	(0.0076) **	(0.0051) **	(0.0051) **	(0.0050) **		
nlc	-1.81E-05	-1.82E-05	-1.75E-05	-1.78E-05	-1.77E-05	-1.61E-05	-1.61E-05
	(0.000006) **	(0.000006) **	(0.000005) **	(0.000005) **	(0.000005) **	(0.000005) **	(0.000005) **
grgdp	-0.1779	-0.1625	-0.1444			-0.2626	-0.2492
	(0.1999)	(0.1954)	(0.1839)			(0.1944)	(0.1946)
gcpi	0.3992	0.3693	0.3470	0.3523	0.4067	0.4187	0.4561
	(0.1975) **	(0.1821) **	(0.1725) **	(0.1643) **	(0.1618) **	(0.1966) **	(0.1939) **
vol_irate	0.0022	0.0022	0.0025	0.0025	0.0023	0.0025	0.0024
	(0.0008) **	(0.0008) **	(0.0008) **	(0.0008) **	(0.0008) **	(0.0008) **	(0.0008) **
vol_gforex	-0.0332					-0.0587	-0.0587
	(0.0882)					(0.0860)	(0.0861)
vol_grgdp	0.9003	0.9054	0.9120	0.9119	0.8794	0.8896	0.8655
	(0.1543) **	(0.1536) **	(0.1492) **	(0.1457) **	(0.1425) **	(0.1517) **	(0.1494) **
vol_gcpi	1.0485	1.0260	0.9406	1.0306	1.0748	1.0981	1.1427
	(0.3512) **	(0.3460) **	(0.3321) **	(0.3279) **	(0.3267) **	(0.3470) **	(0.3452) **
d1990	0.1358	0.1349	0.1109	0.1079	0.1018	0.1148	0.1002
	(0.0522) **	(0.0522) **	(0.0323) **	(0.0315) **	(0.0314) **	(0.0510) **	(0.0487) **
d1991	0.1442	0.1429	0.1202	0.1178	0.1112	0.1217	0.1066
	(0.0523) **	(0.0522) **	(0.0317) **	(0.0311) **	(0.0308) **	(0.0512) **	(0.0487) **
d1992	0.1278	0.1262	0.1041	0.1014	0.0944	0.1074	0.0921
	(0.0517) **	(0.0516) **	(0.0316) **	(0.0310) **	(0.0306) **	(0.0508) **	(0.0481) *
d1993	0.1357	0.1344	0.1112	0.1082	0.1012	0.1107	0.0949
	(0.0544) **	(0.0543) **	(0.0331) **	(0.0323) **	(0.0319) **	(0.0530) **	(0.0502) *
d1994	0.1159	0.1146	0.0922	0.0889	0.0816	0.0922	0.0761
	(0.0544) **	(0.0543) **	(0.0329) **	(0.0322) **	(0.0317) **	(0.0530) *	(0.0501)
d1995	0.1113	0.1101	0.0868	0.0836	0.0759	0.0877	0.0709
	(0.0537) **	(0.0537) **	(0.0319) **	(0.0313) **	(0.0306) **	(0.0527) *	(0.0495)
d1996	0.1040	0.1029	0.0791	0.0754	0.0673	0.0805	0.0632
	(0.0539) *	(0.0539) *	(0.0316) **	(0.0310) **	(0.0303) **	(0.0530)	(0.0496)
d1997	0.1218	0.1200	0.0954	0.0917	0.0842	0.0974	0.0806
	(0.0543) **	(0.0541) **	(0.0314) **	(0.0308) **	(0.0303) **	(0.0532) *	(0.0501) *
d1998	0.1663	0.1645	0.1396	0.1375	0.1300	0.1385	0.1216
	(0.0552) **	(0.0550) **	(0.0319) **	(0.0317) **	(0.0311) **	(0.0539) **	(0.0507) **
d1999	0.1832	0.1814	0.1549	0.1513	0.1435	0.1524	0.1346
	(0.0565) **	(0.0563) **	(0.0319) **	(0.0314) **	(0.0307) **	(0.0550) **	(0.0516) **
d2000	0.1751	0.1734	0.1477	0.1442	0.1361	0.1467	0.1287
	(0.0547) **	(0.0545) **	(0.0310) **	(0.0304) **	(0.0297) **	(0.0535) **	(0.0498) **
d2001	0.1578	0.1561	0.1309	0.1283	0.1207	0.1302	0.1126
	(0.0539) **	(0.0538) **	(0.0307) **	(0.0303) **	(0.0297) **	(0.0529) **	(0.0494) **
d2002	0.1449	0.1429	0.1176	0.1148	0.1072	0.1197	0.1025
	(0.0533) **	(0.0530) **	(0.0307) **	(0.0303) **	(0.0297) **	(0.0523) **	(0.0489) **
d2003	0.1185	0.1164	0.0905	0.0871	0.0797	0.0928	0.0753
	(0.0553) **	(0.0550) **	(0.0314) **	(0.0308) **	(0.0303) **	(0.0541) *	(0.0508)
Det residual covariance	2.29E-38	2.36E-38	2.01E-38	1.94E-38	2.06E-38	1.70E-38	1.82E-38
BIC	-86.32	-86.31	-86.49	-86.54	-86.49	-86.64	-86.59

Standard errors reported in parentheses

* Denotes significance at 10%

**Denotes significance at 5%

Table (7)

Estimation Results: SUR Models for Annual Realized Volatilities

	M1	M2	M3	M4	M5	M6
emerging	0.0434	0.0431	0.0407	0.0408	0.0441	0.0435
	(0.0134) **	(0.0131) **	(0.0127) **	(0.0124) **	(0.0137) **	(0.0134) **
transition	-0.0013				-0.0017	
	(0.0182)				(0.0188)	
log(mc)	-0.0116	-0.0114	-0.0116	-0.0112	0.0066	0.0068
	(0.0055) **	(0.0053) **	(0.0053) **	(0.0052) **	(0.0042)	(0.0038) **
log(gdpus)	0.0314	0.0313	0.0312	0.0309		
	(0.0068) **	(0.0068) **	(0.0068) **	(0.0066) **		
nlc	-1.47E-05	-1.46E-05	-1.40E-05	-1.43E-05	-1.03E-05	-1.02E-05
	(0.000006) **	(0.000006) **	(0.000006) **	(0.000006) **	(0.000006) *	(0.000006) *
grgdp	-0.6222	-0.6261	-0.6435	-0.6568	-0.7915	-0.7911
	(0.2442) **	(0.2413) **	(0.2388) **	(0.2322) **	(0.2474) **	(0.2444) **
gcpi	0.1598	0.1633	0.1442		0.1911	0.1912
	(0.2159)	(0.2094)	(0.2039)		(0.2232)	(0.2171)
vol_irate	0.0040	0.0040	0.0040	0.0043	0.0045	0.0045
	(0.0010) **	(0.0009) **	(0.0008) **	(0.0008) **	(0.0010) **	(0.0010) **
vol_gforex	0.1329	0.1319	0.1295	0.1649	0.1344	0.1342
	(0.1057)	(0.1054)	(0.1011)	(0.0894) *	(0.1078)	(0.1074)
vol_grgdp	0.6500	0.6508	0.6593	0.7002	0.3641	0.6154
	(0.1437) **	(0.1416) **	(0.1413) **	(0.1277) **	(0.1474) **	(0.1455) **
vol_gcpi	-0.0432	-0.0446			-0.0061	-0.0088
	(0.3978)	(0.3942)			(0.4078)	(0.4038)
d1990	0.4158	0.4134	0.4168	0.4133	0.3776	0.3749
	(0.0512) **	(0.0478) **	(0.0475) **	(0.0471) **	(0.0513) **	(0.0477) **
d1991	0.3726	0.3703	0.3738	0.3702	0.3341	0.3316
	(0.0489) **	(0.0454) **	(0.0451) **	(0.0447) **	(0.0497) **	(0.0460) **
d1992	0.3583	0.3561	0.3595	0.3551	0.3246	0.3222
	(0.0493) **	(0.0459) **	(0.0456) **	(0.0451) **	(0.0502) **	(0.0466) **
d1993	0.3492	0.3468	0.3509	0.3457	0.3087	0.3060
	(0.0500) **	(0.0464) **	(0.0460) **	(0.0455) **	(0.0505) **	(0.0467) **
d1994	0.3616	0.3593	0.3633	0.3570	0.3211	0.3185
	(0.0502) **	(0.0463) **	(0.0460) **	(0.0454) **	(0.0507) **	(0.0467) **
d1995	0.3439	0.3416	0.3448	0.3403	0.3030	0.3003
	(0.0513) **	(0.0473) **	(0.0471) **	(0.0464) **	(0.0521) **	(0.0480) **
d1996	0.3194	0.3174	0.3205	0.3186	0.2796	0.2773
	(0.0502) **	(0.0461) **	(0.0458) **	(0.0452) **	(0.0511) **	(0.0468) **
d1997	0.4102	0.4079	0.4120	0.4090	0.3689	0.3664
	(0.0509) **	(0.0468) **	(0.0464) **	(0.0458) **	(0.0518) **	(0.0474) **
d1998	0.4656	0.4633	0.4669	0.4630	0.4194	0.4169
	(0.0515) **	(0.0474) **	(0.0471) **	(0.0464) **	(0.0522) **	(0.0479) **
d1999	0.4136	0.4114	0.4152	0.4117	0.3641	0.3616
	(0.0524) **	(0.0481) **	(0.0478) **	(0.0471) **	(0.0530) **	(0.0485) **
d2000	0.4276	0.4254	0.4293	0.4259	0.3818	0.3793
	(0.0512) **	(0.0470) **	(0.0466) **	(0.0460) **	(0.0520) **	(0.0474) **
d2001	0.4157	0.4135	0.4170	0.4131	0.3693	0.3669
	(0.0505) **	(0.0464) **	(0.0461) **	(0.0454) **	(0.0512) **	(0.0469) **
d2002	0.4068	0.4046	0.4084	0.4048	0.3620	0.3597
	(0.0504) **	(0.0465) **	(0.0461) **	(0.0456) **	(0.0511) **	(0.0470) **
d2003	0.3616	0.3594	0.3632	0.3589	0.3170	0.3145
	(0.0518) **	(0.0478) **	(0.0474) **	(0.0467) **	(0.0525) **	(0.0483) **
Det residual covariance	3.58E-37	3.61E-37	3.59E-37	3.57E-37	5.11E-37	5.17E-37
BIC	-83.5805	-83.5853	-83.6048	-83.6278	-83.2415	-83.2437

Standard errors reported in parentheses

* Denotes significance at 10%

**Denotes significance at 5%

Table (8)

Estimation Results: SUR Models for Log Long Run Volatilities

	M1	M2	M3	M4	M5	M6	M7
emerging	0.1847	0.1893	0.1943	0.1873	0.2009	0.1871	0.1824
	(0.0625) **	(0.0618) **	(0.0614) **	(0.0596) **	(0.0557) **	(0.0630) **	(0.0614) **
transition	-0.0341	-0.0353	-0.0355			-0.0258	
	(0.0768)	(0.0762)	(0.0758)			(0.0778)	
log(mc)	-0.0190	-0.0162	-0.0163	-0.0135		0.0336	0.0357
	(0.0248)	(0.0244)	(0.0242)	(0.0235)		(0.0178) **	(0.0167) **
log(gdpus)	0.0943	0.0900	0.0915	0.0913	0.0776		
	(0.0319) **	(0.0313) **	(0.0309) **	(0.0310) **	(0.0217) **		
nlc	-7.98E-05	-7.90E-05	-7.99E-05	-7.91E-05	-7.67E-05	-6.84E-05	-6.78E-05
	(0.000023) **	(0.000023) **	(0.000023) **	(0.000023) **	(0.000022) **	(0.000022) **	(0.000022) **
grgdp	0.1296					-0.2614	-0.2502
	(0.7567)					(0.7585)	(0.7581)
gcpi	1.1551	1.0783	0.8944	0.9476	0.9377	1.2364	1.2781
	(0.7910)	(0.7716)	(0.6795)	(0.6732)	(0.6501)	(0.8012)	(0.7921) *
vol_irate	0.0066	0.0067	0.0065	0.0064	0.0071	0.0080	0.0079
	(0.0032) **	(0.0032) **	(0.0030) **	(0.0030) **	(0.0029) **	(0.0033) **	(0.0033) **
vol_gforex	-0.0866	-0.1207				-0.1741	-0.1758
	(0.3435)	(0.3325)				(0.3434)	(0.3434)
vol_grgdp	2.6746	2.7075	2.6850	2.6227	2.6038	2.5280	2.4859
	(0.6386) **	(0.6312) **	(0.6270) **	(0.6123) **	(0.5994) **	(0.6341) **	(0.6212) **
vol_gcpi	3.1302	3.2913	3.1968	3.2719	3.0602	3.2715	3.3195
	(1.3760) **	(1.3545) **	(1.3308) **	(1.3249) **	(1.2945) **	(1.3854) **	(1.3789) **
d1990	-1.8925	-1.8987	-1.9016	-1.9304	-2.0139	-1.9710	-1.9928
	(0.2141) **	(0.2119) **	(0.2105) **	(0.2015) **	(0.1373) **	(0.2138) **	(0.2035) **
d1991	-1.8700	-1.8750	-1.8811	-1.9108	-1.9911	-1.9578	-1.9801
	(0.2140) **	(0.2119) **	(0.2103) **	(0.2007) **	(0.1339) **	(0.2144) **	(0.2037) **
d1992	-1.9515	-1.9569	-1.9652	-1.9953	-2.0730	-2.0280	-2.0506
	(0.2120) **	(0.2100) **	(0.2083) **	(0.1983) **	(0.1344) **	(0.2131) **	(0.2019) **
d1993	-1.9502	-1.9563	-1.9627	-1.9939	-2.0751	-2.0444	-2.0680
	(0.2203) **	(0.2182) **	(0.2165) **	(0.2062) **	(0.1359) **	(0.2198) **	(0.2080) **
d1994	-2.0314	-2.0368	-2.0430	-2.0758	-2.1533	-2.1235	-2.1481
	(0.2229) **	(0.2209) **	(0.2192) **	(0.2080) **	(0.1384) **	(0.2225) **	(0.2098) **
d1995	-2.0532	-2.0625	-2.0697	-2.1038	-2.1825	-2.1454	-2.1710
	(0.2201) **	(0.2181) **	(0.2165) **	(0.2040) **	(0.1338) **	(0.2212) **	(0.2074) **
d1996	-2.0872	-2.0965	-2.1045	-2.1394	-2.2200	-2.1783	-2.2046
	(0.2208) **	(0.2188) **	(0.2172) **	(0.2042) **	(0.1328) **	(0.2224) **	(0.2079) **
d1997	-1.9937	-2.0021	-2.0123	-2.0465	-2.1293	-2.0909	-2.1165
	(0.2210) **	(0.2190) **	(0.2173) **	(0.2049) **	(0.1313) **	(0.2222) **	(0.2084) **
d1998	-1.8209	-1.8312	-1.8413	-1.8765	-1.9612	-1.9327	-1.9589
	(0.2233) **	(0.2214) **	(0.2195) **	(0.2065) **	(0.1316) **	(0.2238) **	(0.2094) **
d1999	-1.7552	-1.7659	-1.7761	-1.8128	-1.9010	-1.8817	-1.9092
	(0.2284) **	(0.2263) **	(0.2245) **	(0.2106) **	(0.1307) **	(0.2285) **	(0.2130) **
d2000	-1.7733	-1.7834	-1.7932	-1.8297	-1.9150	-1.8885	-1.9158
	(0.2221) **	(0.2200) **	(0.2183) **	(0.2041) **	(0.1276) **	(0.2228) **	(0.2070) **
d2001	-1.8307	-1.8416	-1.8525	-1.8881	-1.9708	-1.9444	-1.9711
	(0.2194) **	(0.2173) **	(0.2154) **	(0.2017) **	(0.1275) **	(0.2204) **	(0.2053) **
d2002	-1.8914	-1.9009	-1.9121	-1.9471	-2.0305	-1.9937	-2.0201
	(0.2172) **	(0.2151) **	(0.2132) **	(0.1997) **	(0.1284) **	(0.2184) **	(0.2034) **
d2003	-2.0018	-2.0122	-2.0241	-2.0599	-2.1442	-2.1068	-2.1337
	(0.2252) **	(0.2231) **	(0.2210) **	(0.2075) **	(0.1318) **	(0.2263) **	(0.2112) **
Det residual cov	1.15E-21	1.15E-21	1.19E-21	1.24E-21	1.05E-21	9.52E-22	9.76E-22
BIC	-47.8729	-47.8879	-47.8704	-47.8398	-48.0193	-48.0808	-48.0688

Standard errors reported in parentheses

* Denotes significance at 10%

**Denotes significance at 5%