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

Robert F. Engle
Stern School of Business, New York University
rengle@stern.nyu.edu

Jose Gonzalo Rangel
Department of Economics, UCSD
jgrangel@ucsd.edu

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ABSTRACT

25 years of volatility research has left the macroeconomic environment playing a minor role. This paper proposes modeling equity volatilities as a combination of macroeconomic effects and time series dynamics. High frequency return volatility is specified to be the product of a slow moving deterministic component, represented by an exponential spline, and a unit GARCH. This deterministic component is the unconditional volatility, which is then estimated for nearly 50 countries over various sample periods of daily data.

Unconditional volatility is then modeled as an unbalanced panel with a variety of dependence structures. It is found to vary over time and across countries with high unconditional volatility resulting from high volatility in the macroeconomic factors GDP, inflation and short term interest rate, and with high inflation and slow growth of output. Volatility is higher for emerging markets and for markets with small numbers of listed companies and market capitalization, but also for large economies.

The model allows long horizon forecasts of volatility to depend on macroeconomic developments, and delivers estimates of the volatility to be anticipated in a newly opened market.

1. Introduction

After more than 25 years of research on volatility, the central unsolved problem is the relation between the state of the economy and aggregate financial volatility. The number of models that have been developed to predict volatility based on time series information is astronomical, but the models that incorporate economic variables are hard to find. Using various methodologies, links are found but they are generally much weaker than seems reasonable. For example, it is widely recognized that volatility is higher during recessions and following announcements but these effects turn out to be a small part of measured volatility.

Officer(1973) tried to explain the high volatility during the 30's based on leverage and the volatility of industrial production. Schwert(1989) sought linkages between financial volatility and macro volatility but concluded that "The puzzle highlighted by the results in this paper is that stock volatility is not more closely related to other measures of economic volatility."

An alternative approach examines the effects of news or announcements on returns. With simple or elaborate regression models, contemporaneous news events are included in return regressions. Roll(1988), and Cutler Poterba and Summers(1990) for example developed such models which are found to explain only a fraction of volatility ex post, and more recent versions such as Andersen and Bollerslev(1998a), Fleming and

Remolona(1999), Balduzzi, Elton and Green(2001), or Andersen Bollerslev Diebold and Varga(2005) use intraday data but with more or less similar results.

This paper will introduce a simple model of the relation between macroeconomics and volatility and then apply this to the problem of explaining the financial volatility of 50 markets over time. Along the way a new volatility model, the SPLINE GARCH, will be introduced to allow the high frequency financial data to be linked with the low frequency macro data. As a result it will be possible to forecast the effect of potential macroeconomic events on equity volatility and to forecast the volatility that could be expected in a new market. Moreover, the assumption that volatility is mean reverting to a constant level, which underlies almost all GARCH and SV models estimated over the last 25 years, will be relaxed by the SPLINE GARCH model.

This paper is organized as follows. In section 2, we describe a model of financial volatility in a macroeconomic environment. In section 3, we introduce the Spline-GARCH model for unconditional volatility. Section 4 presents a description of the data followed by a discussion on the definition and construction of the variables involved in the cross-sectional analysis. In section 5, we motivate the econometric approach for the cross-sectional analysis and discuss the estimation results of the determinants of long run volatilities. In section 6, we analyze the effects of country heterogeneity in our results. Section 7 presents a further robustness analysis with estimation of alternative models using other proxies for unconditional volatilities. Section 8 provides concluding remarks.

2. A Model of Financial Volatility in a Macroeconomic Environment

The now highly familiar log linearization of Campbell(1991) and Campbell and Shiller(1988) delivers an easy expression for the surprise in the return to a financial asset. Let r be the log return and d be the log dividend from owning the asset from time t-1 through t. Then

(1) $$r_t - E_{t-1}(r_t) = (1-\rho)\sum_{j=0}^{\infty}\rho^j (E_t - E_{t-1})(d_{t+1+j}) - \sum_{j=0}^{\infty}\rho^j (E_t - E_{t-1})(r_{t+1+j})$$

which can be written as

(2) $$r_t - E_{t-1}r_t = \eta_t^d - \eta_t^r$$

Unexpected returns can be decomposed into shocks to future cash flows or shocks to future expected returns. Shocks to dividends have a positive effect on returns while shocks to interest rates or risk premiums have a negative effect. Different news events may have very different impacts on returns depending on whether they have only a short horizon effect or a long horizon effect.

In order to explain the size of these shocks, much research has decomposed unexpected returns into its news components. Equation (2) can be written as

(3) $$r_t - E_{t-1}r_t = \sum_{i=1}^{K}\beta_i z_{t,i} e_{t,i}$$

where there are K news sources. The magnitude of the news event is indicated by *e* which could be the difference between prior expected values and the announced value. It is clear that announcements cannot be the only source of news since the gradual accumulation of evidence prior to the actual announcement, must also affect prices. The effect of this news on stock prices may depend upon the state of the economy as given by $z_{i,t}$. For example, bad news about a firm may be more influential in a recession than in a growth period as the firm may be closer to bankruptcy.

This model is only useable if the news is observable. If it is not, then equation (3) has only one innovation that represents all the news. The multiplicative factor $\tau_1\left(\vec{z}_t\right)$ aggregates all the relevant macroeconomic inputs.

$$r_t - E_{t-1}r_t = \sqrt{\tau_1\left(\vec{z}_t\right)}u_t \tag{4}$$

The variance of this innovation will again depend upon macro factors, partly because the size of the news will depend upon these variables and partly because the intensity of news arrivals will also depend upon macroeconomics. This can be written as

$$V\left(u_t\right) = \tau_2\left(\vec{z}_t\right) \tag{5}$$

where either the macroeconomic variables z are treated as deterministic or the variance is calculated conditional on the macroeconomy. The innovation u, may however have temporal dependence that is not due to macroeconomics. Suppose the remaining heteroskedasticity is modeled by a GARCH process with unit unconditional variance. Then

$$u_t = \sqrt{\tau_2\left(\vec{z}_t\right)g_t}\;\varepsilon_t \tag{6}$$

where both g and ε^2 have unit unconditional expectation. Substituting (6) into (4) gives

$$r_t - E_{t-1}r_t = \sqrt{\tau_1\left(\vec{z}_t\right)\tau_2\left(\vec{z}_t\right)g_t}\;\varepsilon_t \tag{7}$$

Clearly the macroeconomic effects on volatility derive from both the variance of the news and the multiplier of the news, however these cannot be separately identified unless the news is observable.

One approach is to estimate (7) directly by specifying a relationship for the unconditional variance. This is the approach to be introduced in this paper. A second approach is to calculate the realized variance over a time period and then model the relation between this value and the macro variables. The realized variance is given by its expected value plus a mean zero error term with unspecified properties. This gives

$$\hat{\sigma}_T^2 = \sum_{t=1}^{T} \left(r_t - E_{t-1} r_t \right)^2 = \sum_{t=1}^{T} \tau_1 \left(\vec{z}_t \right) \tau_2 \left(\vec{z}_t \right) + w_T \tag{8}$$

It is clear that there is an error term in (8) that will make estimation less precise but still unbiased.

In practice, direct estimation of (7) is not convenient as the macro variables are not defined for each high frequency date. Use of quarterly values will lead to breaks at the end of quarters that will have no economic meaning. Instead, we introduce a partially non-parametric approximation to the macro variables. It reflects the fact that they are slowly changing. This has the great advantage that it can be used for any series without requiring specification of the economic structure. The estimated unconditional variances can then be fitted on a low frequency basis to the macro determinants just as in (8). This SPLINE GARCH model is introduced in the next section.

3. 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. 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:

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

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

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

where,

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

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

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 unspecified, 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 coefficient, $\{w_i\}$. 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:

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

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 (11) describes, non-parametrically, the long term dynamics of volatility with a smooth differentiable curve 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 volatility trend suggested by the data reveals a cyclical behavior that may be associated with the business cycle. In addition, the graph shows that the assumption 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 unconditional volatility presented in equation (12).

4. 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

[1] See Andersen and Bollerslev (1998b).

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.

4.1 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 unconditional 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 select the optimal number of knots associated with the spline component. In each case, we obtain the unconditional expected volatility described in equation (12). 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 constraints 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 unconditional 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

[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).

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.

$$
\begin{aligned}
&\Delta \log\left(y_t\right) = c + u_t, \quad u_t = \rho u_{t-1} + e_t \\
&\sigma_{y,t}^2 = \frac{1}{4} \sum_{j=t-2}^{t+1} \left|e_j\right|
\end{aligned}
\tag{13}
$$

Following the same setup, we construct 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 of market capitalization to

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.

5. 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 to 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),

$$(14) \qquad Uvol_{i,t} = x'_{i,t}\beta_t + u_{i,t},\ t = 1,2,...,T,\ i = 1,2,...,N_t$$

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 such correlations for unconditional 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

[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 is suggested in Schwert (1989). However when SUR estimation is used, the assumption of exogeneity will be maintained

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.[6] 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. Standard 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 the standard random effects model allows 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). Therefore, more general panel data approaches that deal more efficiently with serial correlation would be desirable. We will explore one possibility in the robustness section. Nevertheless, given

[6] Cross sectional dependence will generally not give inconsistency in our model, but inference and efficiency could be improved if a factor structure is assumed as in Pesaran(2005).

that the SUR method allows for time fixed effects and flexible autocorrelation structure, we take this approach as our main specification for the cross sectional analysis. We assume that the coefficients, other than the intercept, remain constant over time. 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.[7] From this preliminary analysis, we observe positive relations among unconditional market volatilities and each of the following variables: emerging markets, log nominal GDP, inflation rate, 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 and market size variables, such as log market capitalization, 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 (14), 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

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

only slightly larger volatility than developed economies. Market size variables show different results. Whereas log market capitalization has a significant negative effect (at the 10% level), log nominal GDP in current US dollars is positive and significant (at the 5% level). 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 rates also affect 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 real 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 real 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, small and quite insignificant. This 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. We estimate different model specifications based on a reduction process that drops the least significant variable one at a time. 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. In column 2 of table (7), we present the "best" reduction in which the BIC favors a specification for which volatility of exchange rates (first) and real GDP growth (second) are omitted. Therefore, the reduction process leads to a model with nine explanatory variables.

6. Country Heterogeneity

We start this section with a diagnostic analysis estimating the benchmark SUR model excluding from the sample one country at a time. Figures 3 and 4 show the coefficients associated with each regressor and the t-statistics respectively. Each point in the horizontal axis represents the country that is dropped from the sample following the order presented in table (1). For instance, the first point corresponds to the estimation without Argentina, and the last point corresponds to the estimation without Venezuela. From figure 4, we observe that the significance of some explanatory variables remains strong no matter which country is taken out of the sample. Indeed, this is the case for emerging, number of listings, log nominal GDP, and volatility of real GDP, which also preserve the same sign (see panels 1, 4, 5, and 10, figures 3 and 4). In contrast, a surprising result arises with respect to real GDP growth and volatility of inflation. When we remove Argentina from the sample, volatility of inflation is no longer significant and changes sign (see panel 11, figures 3 and 4); at the same time, real GDP growth becomes significant with a considerably larger negative sign (see panel 6, figures 3 and 4).

Argentina seems to be an influential observation for other variables as well. For instance, volatility of interest rates becomes highly significant when this country is dropped from the sample. Moreover, although other observations such as Czech Republic and Russia seem to be influential for the significance of this variable (see panel 8, figure 4), the effect of these countries is no longer influential once Argentina is taken out of the sample. Thus, without Argentina, volatility of interest rate is significant at 5% level no matter which other country is omitted. Something similar occurs with inflation; indeed, the apparent influential effects on the significance of inflation of countries such as Lithuania, Peru, and Turkey are drastically diminished once Argentina is out of the sample.[8]

Column 4 of table (6) presents estimation results of the SUR model when Argentina is removed from the sample. As shown in figures 3 and 4, the main differences with respect

[8] Inflation remains significant at 5% when either Lithuania or Turkey is dropped from the sample without Argentina. For Peru, the variable is significant only at 13%.

to column 1 include the loss of log market capitalization and volatility of inflation as significant explanatory variables, and the gain of real GDP growth as a significant variable. From these diagnostics we find that the results for six variables, namely emerging, log nominal GDP, number of listings, inflation, volatility of interest rates, and volatility of real GDP growth, are quite robust. Regarding real GDP growth and volatility of inflation, the results presented in the previous section should be taken with caution given the sensitivity of the corresponding estimates to the inclusion of Argentina in the sample.

However, dropping Argentina from the sample might be unsatisfactory not only because this country is an important emerging market in which the relation between macroeconomic environment and financial volatility might be of particular interest (especially during the period surrounding the recent Argentine crisis, 2001-2002), but also because looking at the macroeconomic time series of Argentina, we did not find a conclusive argument to support the deletion of this country.

Therefore, we explore the possibility of giving more structure to the unobserved individual country effects in order to evaluate their possible impacts in our results. Specifically, we estimate an alternative panel data model that accounts for individual country random effects, keeping the time fixed effects, and allows for serial correlation in the remainder error term using a simple first order autoregressive process.[9] In fact, this

[9] References for panel data models with serial correlation include Lillard and Willis (1978), Baltagi and Li (1991), and Chamberlain (1984).

reflects the effect of unobserved variables that are serially correlated across time. Thus, the error term in equation (14) is modeled as follows:

(15) $$u_{i,t} = \lambda_t + \mu_i + \nu_{i,t}$$

where

$$\begin{aligned}
&\lambda_t = \text{time fixed effects} \\
&\mu_i \sim iid(0, \sigma_\mu) \\
&\nu_{i,t} = \rho \nu_{i,t-1} + \varepsilon_{i,t} \\
&\varepsilon_{i,t} \sim iid(0, \sigma_\varepsilon) \\
&\varepsilon_{i,t} \perp \mu_i
\end{aligned}$$

Estimation results for this model are shown in the last column of table (6). We confirm the robustness of our results with respect to the six variables mentioned above. Moreover, in this case neither real GDP growth nor volatility of inflation is significant. Interestingly, even though all countries were included in the sample, these results look quite similar to those in column 4, corresponding to the SUR model without Argentina. Therefore, modeling random country effects seems to account for the effect of unobservables associated with influential observations.[10]

[10] Specifications with fixed country effects were also considered; however, as we expected from our earlier discussion about the little time variability observed in most of our explanatory variables, the Hausman (1978) test rejected in general fixed effects specifications in favor of random effects models.

7. Realized Volatility

We continue our robustness analysis by comparing 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 to the following system:

$$(16) \qquad realized\_volatility_{i,t} = x'_{i,t}\beta_t + v_{i,t},\ t = 1,2,...,T,\ i = 1,2,...,N_t$$

where the same explanatory variables are included, and $v_{i,t}$ satisfies the same conditions mentioned in section 5. The estimation results for realized volatilities are presented in column 1 of table (7). We observe the same signs for most of the variables with exception of volatility of inflation. Specifically, volatility of inflation shows a negative and insignificant effect on realized volatilities, contrasting with the unconditional volatility case, in which the effect was positive and highly significant.

Column 2 of table (7) shows estimation results for the "best" reduction based on the same criterion described in the previous section. Specifically, for realized volatilities, the least significant variable is the indicator of transition, followed by volatility of inflation, and inflation rate. 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 real GDP growth, a variable that is characterized by its low correlation across time with respect to other explanatory variables.

As in the case of unconditional volatilities, we perform a diagnostic analysis by reestimating the SUR model dropping from the sample one country at a time. Figures 6 and 7 present the estimates and t-statistics respectively. In this case, Argentina also seems to be an influential observation for volatility of inflation and real GDP growth (see panels 6 and 11, figures 5 and 6). Nevertheless, volatility of inflation is never significant and real GDP growth is always significant. Figure 6 suggests that five variables, namely emerging, log nominal GDP, real GDP growth, volatility of interest rates, and volatility of real GDP growth, are always significant at 5% level no matter which country is deleted from the sample. On the other hand, number of listings is sensitive to the inclusion of the UK, and log market capitalization is sensitive to the inclusion of Chile, India, Poland, and South Africa. The last two columns of table 7 confirm this description. The results from a SUR model without Argentina do not change too much with respect to the results in column 1 (including all countries). However, when random country effects are introduced, number of listings and log market capitalization are no longer significant. Just the five variables named above remain significant. Note that four of them, namely emerging, log nominal GDP, volatility of interest rates, and volatility of real GDP growth, coincide with the "robust" variables in the unconditional volatility case. Nevertheless, the main difference with respect to this case is maintained. Real GDP growth is always relevant for realized volatility but not for unconditional volatility; and inflation is always significant for unconditional volatility but never for realized volatility.

Moreover, number of listings is also always significant for unconditional volatility, but it is not for realized volatility in the random effects model.

Furthermore, we observe that among the SUR specifications, the determinant of the residual covariance is smaller for the models with unconditional volatility as dependent variable. This may suggest that unconditional volatility fits better in terms of the concentrated likelihood. In addition, table 8 shows the R-squares for each equation in the SUR system for both unconditional and realized volatility. The results point to the same direction that the model using unconditional volatility shows better fit than that using realized volatility. In summary, as is illustrated in figure 2, discrepancies in the results between unconditional and realized volatility might be due to the fact that the latter is a noisier measure of long run volatility.

We also compare the results in levels from the previous sections with the results from a model in logs. Specifically, we estimate two systems of equations, in which the log of both the unconditional volatility from the Spline-model and the annual realized volatility are the dependent variables for each year, respectively. Column 3 in Tables (6) and (7) presents estimation results for these cases. Note that for most of the variables the signs do not change with respect to the models in levels. The only exception is the real GDP growth rate for unconditional volatility, 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.

8. 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 GDP and interest rates, are primary causes of unconditional market volatility. These variables show a strong positive effect in the cross sectional analysis. In addition, volatility of inflation also presents a positive effect, but in this case, the result is sensitive to the inclusion of one country, Argentina. Countries with high inflation and countries with low real growth rate have higher volatility although the importance of real growth also depends on Argentina.

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.

Market size variables are also important. The number of listed companies, as an indicator of the span of local diversification opportunities, reduces unconditional market volatility. In addition, the size of the economies measured by the log of GDP in US dollars increases unconditional volatilities; bigger countries have more volatility.

After performing some diagnostic analyses, we conclude that the results are robust for all variables except volatility of inflation and real GDP growth for which statistical significance is sensitive to influential observations.

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

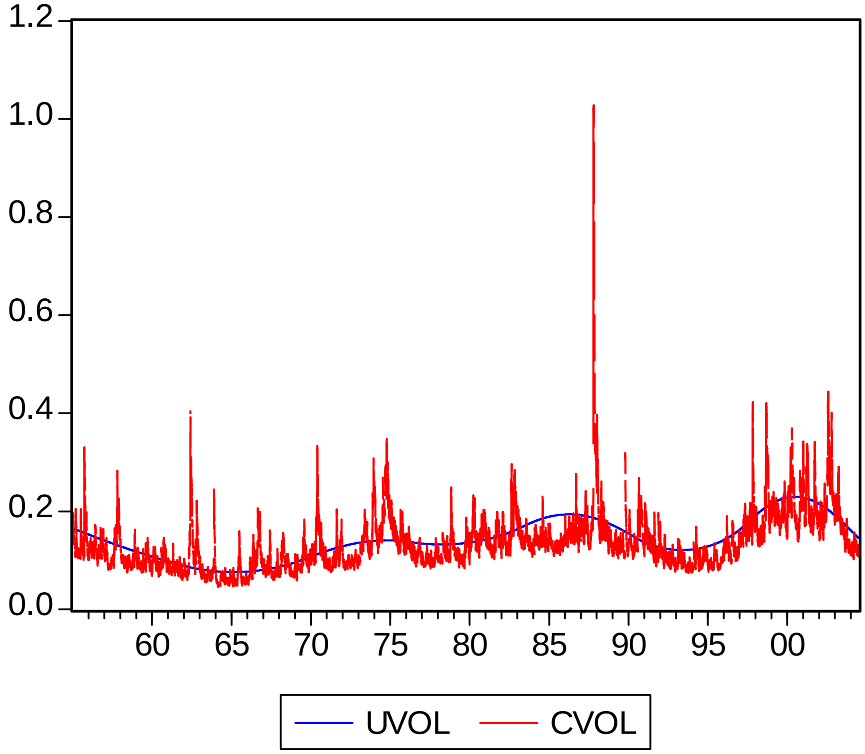

Figure 2
Conditional, Unconditional, and Annual Realized Volatilities of Selected Countries

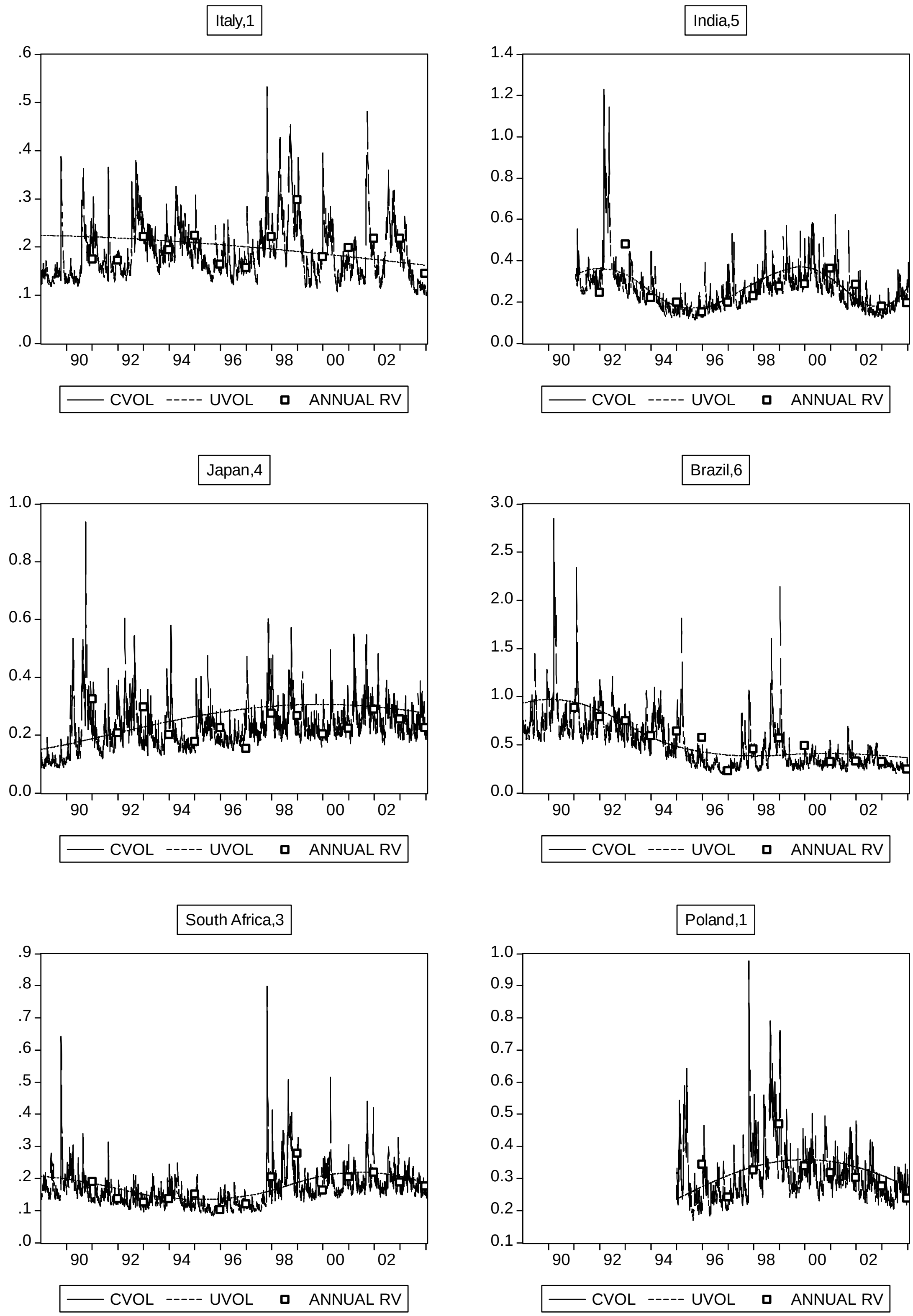

Figure 3
Estimates for Unconditional Volatility: Droping One Country at a Time

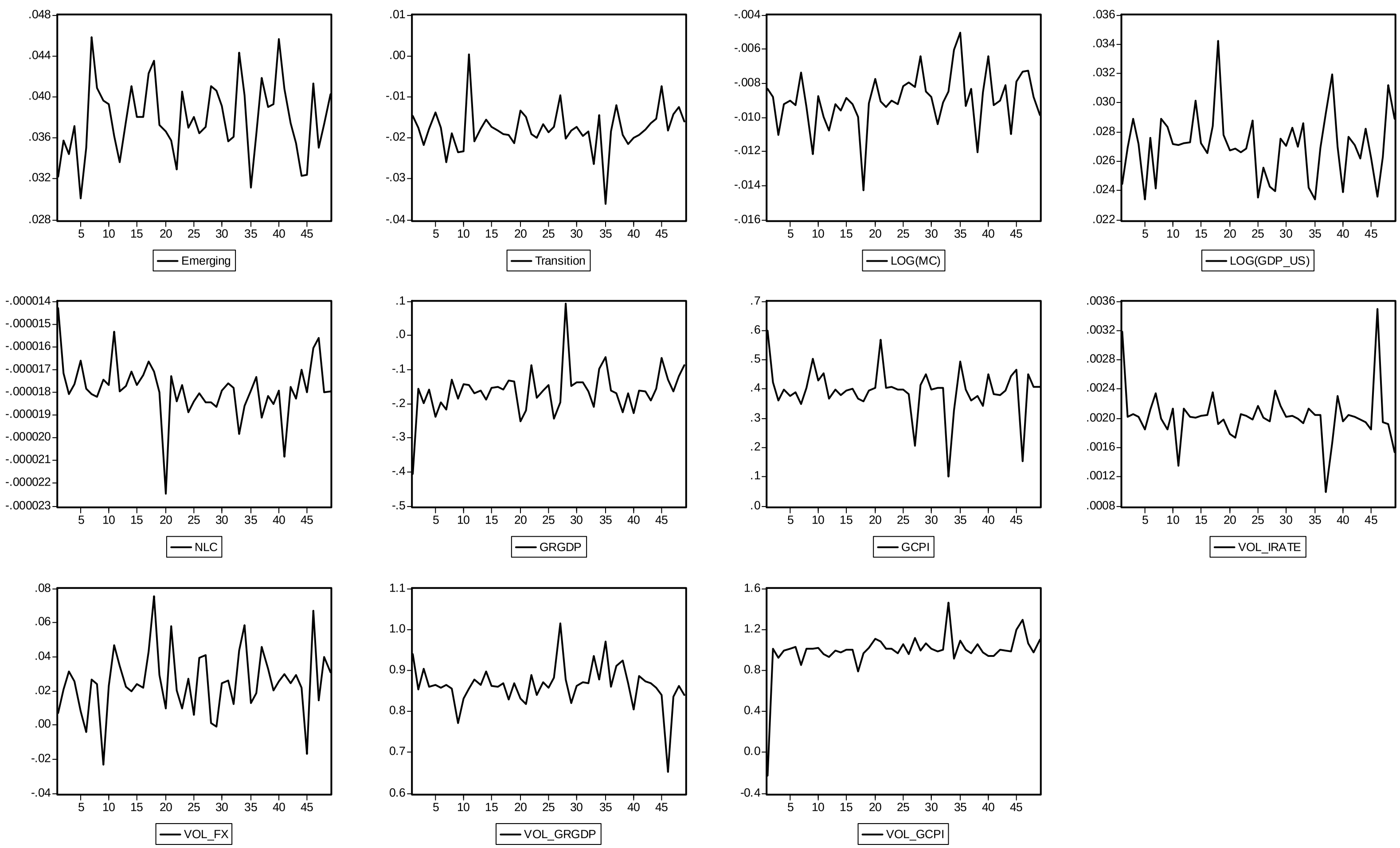

Figure 4
T-Statistics for Unconditional Volatility: Droping One Country at a Time

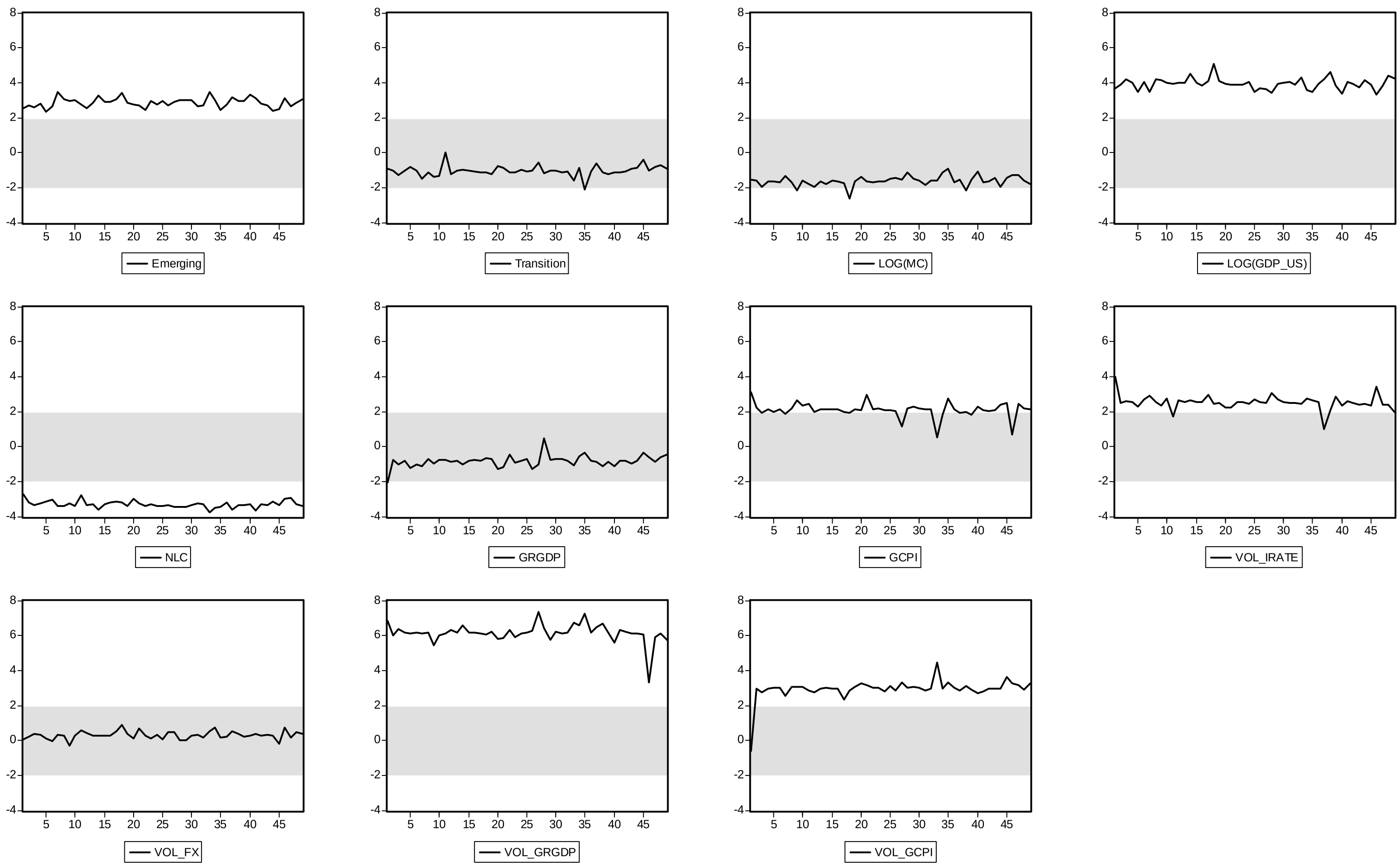

Figure 5
Estimates for Realized Volatility: Droping One Country at a Time

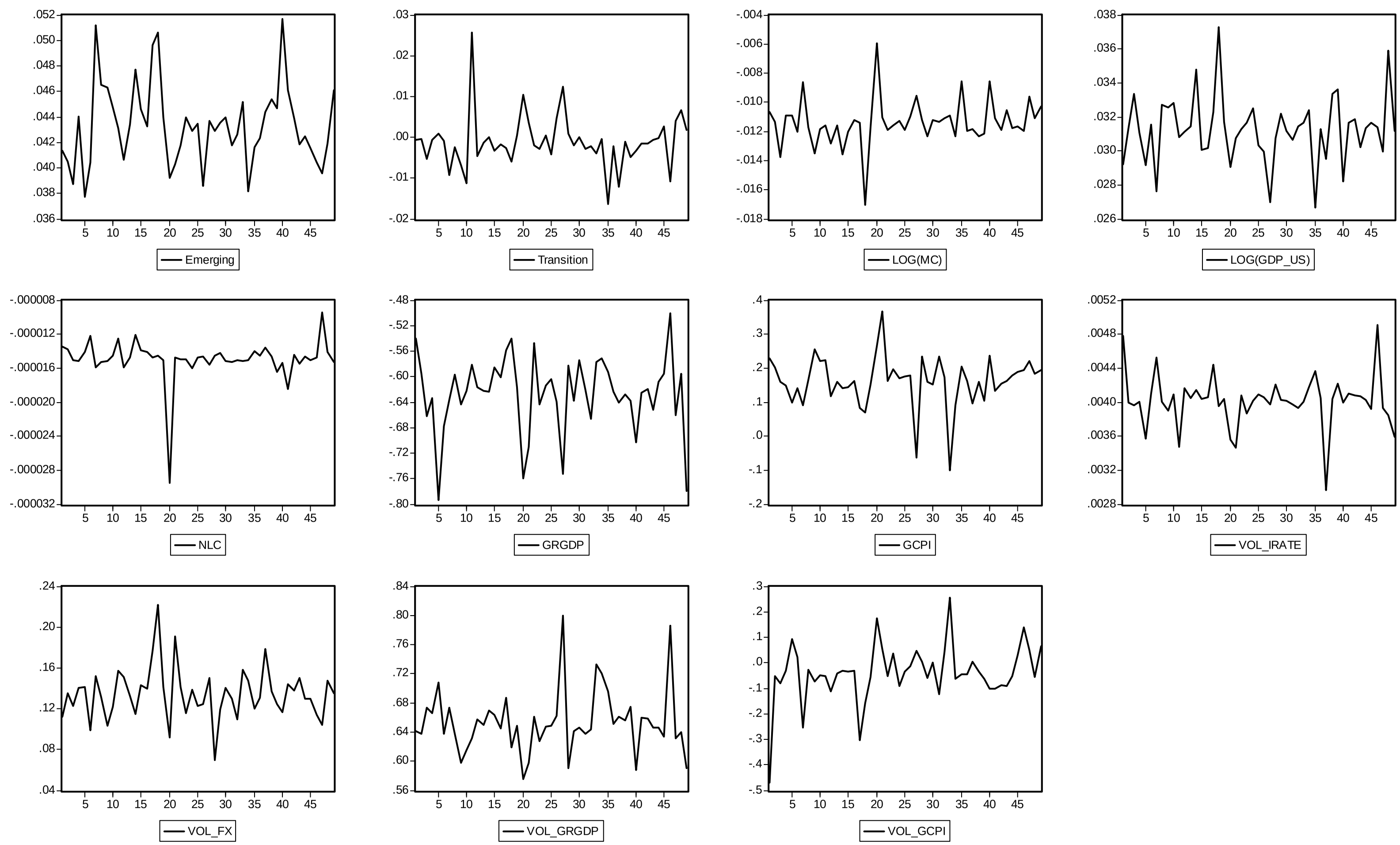

Figure 6
T-Statistics for Realized Volatility: Droping One Country at a Time

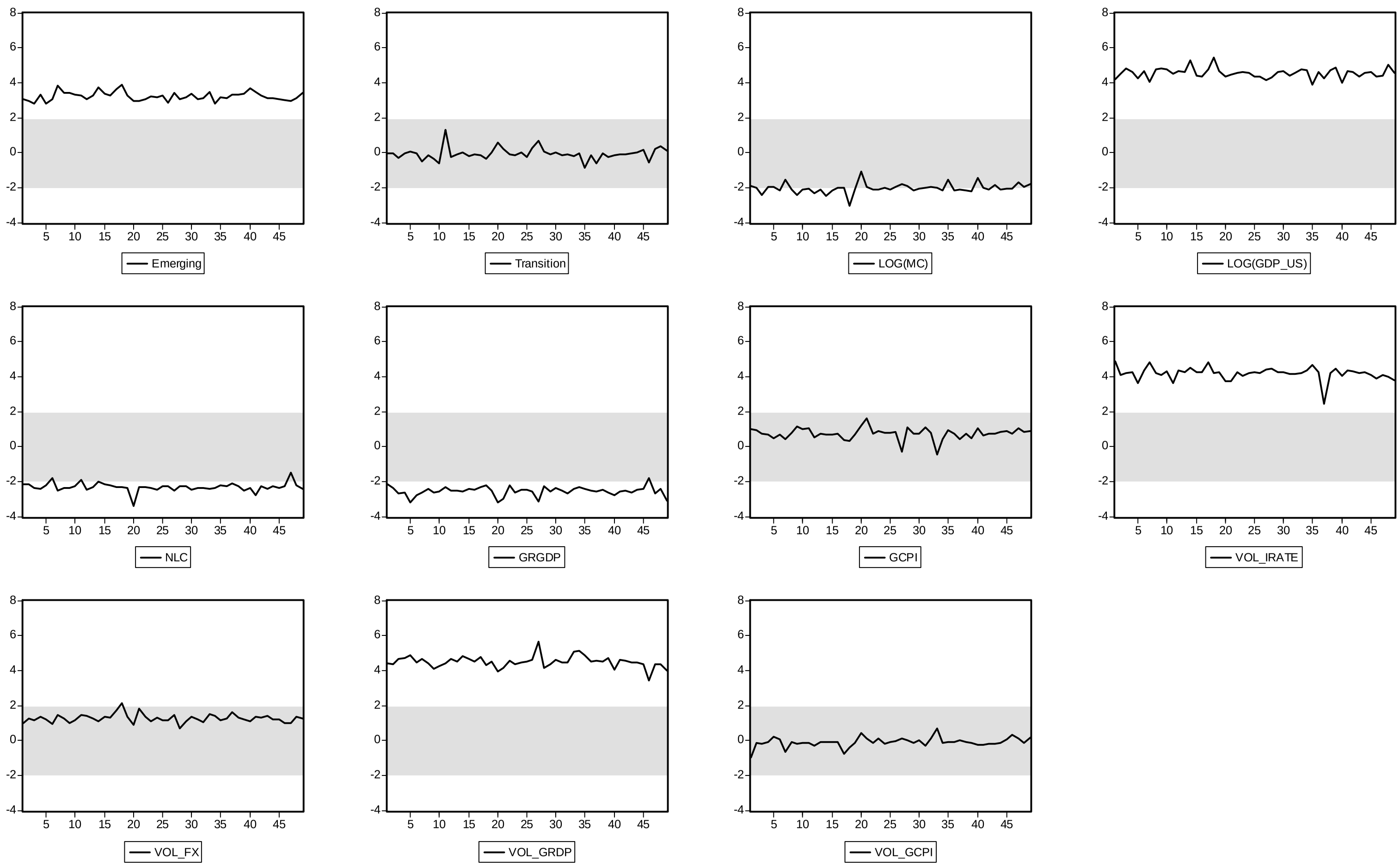

Table (1)

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

	UVOL1997	UVOL1998	UVOL1999	UVOL2000	UVOL2001	UVOL2002	UVOL2003
UVOL1997	1	0.76800	0.79614	0.71752	0.64246	0.66100	0.74651
UVOL1998	0.76800	1	0.91144	0.71398	0.52270	0.49749	0.58763
UVOL1999	0.79614	0.91144	1	0.88333	0.72605	0.68825	0.70021
UVOL2000	0.71752	0.71398	0.88333	1	0.93833	0.87955	0.84312
UVOL2001	0.64246	0.52270	0.72605	0.93833	1	0.94249	0.87678
UVOL2002	0.66100	0.49749	0.68825	0.87955	0.94249	1	0.91471
UVOL2003	0.74651	0.58763	0.70021	0.84312	0.87678	0.91471	1

Table (4)

Correlation of Residuals from Yearly Regressions (1997-2003)

	RES97	RES98	RES99	RES00	RES01	RES02	RES03
RES97	1	0.72148	0.58690	0.63573	0.52845	0.51425	0.66501
RES98	0.72148	1	0.76567	0.70793	0.50636	0.46868	0.49255
RES99	0.58690	0.76567	1	0.76222	0.49994	0.54647	0.47898
RES00	0.63573	0.70793	0.76222	1	0.90622	0.82757	0.78706
RES01	0.52845	0.50636	0.49994	0.90622	1	0.89690	0.82175
RES02	0.51425	0.46868	0.54647	0.82757	0.89690	1	0.85353
RES03	0.66501	0.49255	0.47898	0.78706	0.82175	0.85353	1

Table (5)

Individual SUR Regressions

	Coefficient	Std. Error	t-Statistic	Prob.	Det Residual Covariance
emerging	0.0957	0.0176	5.4528	0.0000	6.45E-39
transition	-0.0077	0.0180	-0.4284	0.6685	1.53E-38
log(mc)	-0.0093	0.0032	-2.9345	0.0035	3.76E-38
log(gdp_dll)	0.0015	0.0055	0.2740	0.7842	2.18E-37
nlc	-1.29E-05	0.0000	-2.3706	0.0181	1.23E-37
grgdp	-0.6645	0.1255	-5.2945	0.0000	3.89E-38
gcpi	0.6022	0.0418	14.4181	0.0000	1.64E-38
vol_irate	0.0089	0.0006	14.4896	0.0000	8.59E-39
vol_forex	0.5963	0.0399	14.9468	0.0000	2.47E-38
vol_grgdp	1.1192	0.1008	11.1056	0.0000	8.71E-39
vol_gcpi	0.9364	0.0848	11.0375	0.0000	2.84E-38

Table (6)

Estimation Results for Unconditional Volatilities					
	SUR Models				Panel Specification
	All Countries	Opt. Reduction	Logs	Without Arg	Random Country Effects
emerging	0.0376	0.0387	0.2079	0.0322	0.0478
	(0.0131)**	(0.0128)**	(0.0592)**	(0.0128)**	(0.0212)**
transition	-0.0178	-0.0164	-0.0332	-0.0147	-0.0258
	(0.0171)	(0.0167)	(0.0741)	(0.0163)	(0.0304)
log(mc)	-0.0092	-0.0085	-0.0345	-0.0083	-0.0046
	(0.0055)*	(0.0053)	(0.0235)	(0.0054)	(0.0067)
log(gdpus)	0.0273	0.0271	0.1156	0.0245	0.0175
	(0.0068)**	(0.0066)**	(0.0302)**	(0.0067)**	(0.0099)*
nlc	-1.8E-05	-1.8E-05	-8.1E-05	-1.4E-05	-1.7E-05
	(5.4E-06)**	(5.3E-06)**	(2.3E-05)**	(5.2E-06)**	(8.6E-06)**
grgdp	-0.1603		0.0962	-0.4046	-0.2094
	(0.1930)		(0.7474)	(0.1984)**	(0.2258)
gcpi	0.3976	0.3915	1.1459	0.5985	0.6114
	(0.1865)**	(0.1641)**	(0.7755)	(0.1939)**	(0.2229)**
vol_irate	0.0020	0.0022	0.0061	0.0032	0.0034
	(0.0008)**	(0.0008)**	(0.0031)*	(0.0008)**	(0.0009)**
vol_gforex	0.0222		0.0185	0.0068	-0.0221
	(0.0844)		(0.3383)	(0.0878)	(0.0959)
vol_grgdp	0.8635	0.8373	2.5808	0.9392	0.9019
	(0.1399)**	(0.1352)**	(0.6138)**	(0.1371)**	(0.1862)**
vol_gcpi	0.9981	1.0983	3.1467	-0.2243	-0.0849
	(0.3356)**	(0.3208)**	(1.3431)**	(0.3627)	(0.3917)
d1990	0.1532	0.1471	-1.8546	0.1638	0.0252
	(0.04835)**	(0.0472)**	(0.2068)**	(0.0470)**	(0.0185)
d1991	0.1488	0.1427	-1.8687	0.1569	0.0160
	(0.0480)**	(0.0468)**	(0.2058)**	(0.0465)**	(0.0173)
d1992	0.1314	0.1245	-1.9539	0.1407	0.0004
	(0.0472)**	(0.0459)**	(0.2037)**	(0.0457)**	(0.0170)
d1993	0.1435	0.1362	-1.9398	0.1447	0.0000
	(0.0498)**	(0.0485)**	(0.2118)**	(0.0480)**	(0.0159)
d1994	0.1244	0.1169	-2.0181	0.1314	-0.0138
	(0.0498)**	(0.0484)**	(0.2144)**	(0.0481)**	(0.0152)
d1995	0.1230	0.1150	-2.0304	0.1320	-0.0236
	(0.0490)**	(0.0477)**	(0.2115)**	(0.0476)**	(0.0141)*
d1996	0.1177	0.1087	-2.0580	0.1274	-0.0276
	(0.0491)**	(0.0479)**	(0.2120)**	(0.0476)**	(0.0134)**
d1997	0.1371	0.1284	-1.9570	0.1483	-0.0068
	(0.0495)**	(0.0482)**	(0.2124)**	(0.0479)**	(0.0124)
d1998	0.1831	0.1763	-1.7804	0.1951	0.0455
	(0.0506)**	(0.0493)**	(0.2150)**	(0.0490)**	(0.0121)**
d1999	0.2028	0.1938	-1.7047	0.2164	0.0648
	(0.0517)**	(0.0503)**	(0.2197)**	(0.0502)**	(0.0114)**
d2000	0.1941	0.1851	-1.7241	0.2049	0.0562
	(0.0499)**	(0.0486)**	(0.2135)**	(0.0484)**	(0.0104)**
d2001	0.1762	0.1683	-1.7837	0.1866	0.0406
	(0.0493)**	(0.0479)**	(0.2110)**	(0.0477)**	(0.0094)**
d2002	0.1619	0.1540	-1.8487	0.1701	0.0242
	(0.0487)**	(0.0473)**	(0.2090)**	(0.0471)**	(0.0076)**
d2003	0.1358	0.1272	-1.9588	0.1456	0.0213
	(0.0505)**	(0.0490)**	(0.2167)**	(0.0487)**	(0.1032)
Det residual covariance	2.3E-38	3.8E-39	4.2E-22	1.6E-39	
BIC	-88.067	-88.15	-48.89	-89.00	

Standard errors reported in parentheses

* Denotes significance at 10%

**Denotes significance at 5%

Table (7)

Estimation Results for Realized Volatilities

	SUR Models				**Panel Specification**
	All Countries	Opt. Reduction	Logs	Without Arg	Random Country Effects
emerging	0.0434	0.0408	0.0964	0.0413	0.0373
	(0.0134)**	(0.0124)**	(0.0317)**	(0.0136)**	(0.0199)*
transition	-0.0013		-0.0084	-0.0007	0.0018
	(0.0182)		(0.0417)	(0.0183)	(0.0282)
log(mc)	-0.0116	-0.0112	-0.0256	-0.0107	-0.0042
	(0.0055)**	(0.0052)**	(0.0130)**	(0.0056)*	(0.0074)
log(gdpus)	0.0314	0.0309	0.0730	0.0292	0.0245
	(0.0068)**	(0.0066)**	(0.0162)**	(0.0069)**	(0.0101)**
nlc	-1.5E-05	-1.4E-05	-3.8E-05	-1.3E-05	-1.3E-05
	(6.4E-06)**	(6.2E-06)**	(1.5E-05)**	(6.2E-06)**	(8.8E-06)
grgdp	-0.6222	-0.6568	-0.9639	-0.5400	-1.0773
	(0.2442)**	(0.2322)**	(0.5277)*	(0.2517)**	(0.2939)**
gcpi	0.1598		0.2366	0.2286	0.4299
	(0.2159)		(0.4840)	(0.2312)	(0.2630)
vol_irate	0.0040	0.0043	0.0059	0.0048	0.0056
	(0.0010)**	(0.0008)**	(0.0021)**	(0.0010)**	(0.0011)**
vol_gforex	0.1329	0.1649	0.2807	0.1120	0.1040
	(0.1057)	(0.0894)*	(0.2247)	(0.1105)	(0.1203)
vol_grgdp	0.6500	0.7002	1.3278	0.6414	0.6728
	(0.1437)**	(0.1277)**	(0.3378)**	(0.1463)**	(0.1989)**
vol_gcpi	-0.0432		-0.1124	-0.4683	-0.5073
	(0.3978)		(0.9042)	(0.4700)	(0.4799)
d1990	0.4158	0.4133	-0.9029	0.4187	0.0640
	(0.0512)**	(0.0471)**	(0.1172)**	(0.0515)**	(0.0193)**
d1991	0.3726	0.3702	-0.9944	0.3751	0.0189
	(0.0489)**	(0.0447)**	(0.1142)**	(0.0491)**	(0.0180)
d1992	0.3583	0.3551	-1.0306	0.3610	0.0045
	(0.0493)**	(0.0451)**	(0.1156)**	(0.0494)**	(0.0179)
d1993	0.3492	0.3457	-1.0560	0.3492	0.0008
	(0.0500)**	(0.0455)**	(0.1172)**	(0.0501)**	(0.0168)
d1994	0.3616	0.3570	-1.0243	0.3584	0.0187
	(0.0502)**	(0.0454)**	(0.1173)**	(0.0504)**	(0.0163)
d1995	0.3439	0.3403	-1.0681	0.3406	-0.0083
	(0.0513)**	(0.0464)**	(0.1193)**	(0.0514)**	(0.0151)
d1996	0.3194	0.3186	-1.1212	0.3202	-0.0368
	(0.0502)**	(0.0452)**	(0.1176)**	(0.0504)**	(0.0145)**
d1997	0.4102	0.4090	-0.9139	0.4127	0.0503
	(0.0509)**	(0.0458)**	(0.1184)**	(0.0511)**	(0.0135)**
d1998	0.4656	0.4630	-0.8042	0.4693	0.1095
	(0.0515)**	(0.0464)**	(0.1190)**	(0.0517)**	(0.0134)**
d1999	0.4136	0.4117	-0.9067	0.4168	0.0527
	(0.0524)**	(0.0471)**	(0.1218)**	(0.0526)**	(0.0128)**
d2000	0.4276	0.4259	-0.8772	0.4330	0.0630
	(0.0512)**	(0.0460)**	(0.1191)**	(0.0513)**	(0.0121)**
d2001	0.4157	0.4131	-0.8969	0.4193	0.0481
	(0.0505)**	(0.0454)**	(0.1177)**	(0.0507)**	(0.0114)**
d2002	0.4068	0.4048	-0.9206	0.4088	0.0415
	(0.0504)**	(0.0456)**	(0.1173)**	(0.0506)**	(0.0097)**
d2003	0.3616	0.3589	-1.0160	0.3657	-0.0904
	(0.0518)**	(0.0467)**	(0.1209)**	(0.0521)**	(0.0978)
Det residual covariance	3.6E-37	3.6E-37	1.8E-27	3.0E-37	
BIC	-83.58	-83.63	-61.25	-83.75	

Standard errors reported in parentheses

* Denotes significance at 10%

**Denotes significance at 5%

Table 8

R-Squared Statistics for Each Equation in the SUR System Including All Countries

	Unconditional Vol	Realized Vol
1990	0.5816	0.4019
1991	0.6435	0.5786
1992	0.7293	0.3640
1993	0.6463	0.5102
1994	0.5798	0.5577
1995	0.6689	0.4982
1996	0.7040	0.7218
1997	0.5700	0.4172
1998	0.5608	0.4835
1999	0.4481	0.3878
2000	0.3908	0.2442
2001	0.3477	0.2556
2002	0.3636	0.0985
2003	0.3968	0.2026
Average	**0.5451**	**0.4087**