MODELLING STOCK RETURNS IN 'VOLATILITY-IN-MEAN' FRAMEWORK UNDER UP AND DOWN MARKET MOVEMENTS: A MULTI-COUNTRY STUDY

by

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Dedicated to

My Parents

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Contents

List of Tables

List of Figures

Chapter 1

Introduction

1.1 Introduction

The first chapter of this thesis begins with a brief review of the existing literature on empirical studies on stock returns, especially those in the context of the relationship between risk and return, at both univariate and multivariate levels. In the next section, studies on the relationship between stock return and monetary policy are reviewed. The motivation of this work is discussed in Section 1.4. Finally, the format of the thesis is given in Section 1.5.

1.2 A Brief Review of the Literature on Risk-Return Relationship - Both Univariate and Multivariate Cases

In this section, we first present a brief review of this literature based on univariate analysis of stock returns. This is followed by the same considering the multivariate set-up where returns on several stock markets are modelled together. Thereafter, we briefly mention about some studies where returns are modelled in terms of some exogenous instruments of monetary policy.

1.2.1 Univariate analysis of returns

In the literature on financial economics, one of the most important relationships studied is the one between risk and return. In fact, investors are assumed to evaluate the performance of their investments in terms of two summary statistics that represent the expected gains of a portfolio and its expected risk as determined from asset volatility. Since the seminal paper by Markowitz (1959), the capital asset pricing model (CAPM) has become an important tool in finance for assessment of cost of capital, portfolio performance, portfolio diversification, valuing instruments, and choosing portfolio strategy. Building on Markowitz's work, Sharp (1964) and Black (1972) developed some other versions of CAPM that can be empirically tested.

It is well-known that the CAPM assumes the risk to be constant. However, this assumption of constant risk was found to be very restrictive, particularly in the context of financial time series. In fact, it has been recognized as early as in 1960's by Mandelbrot (1963), and Fama (1965), that uncertainty in speculative prices, as measured by variances and covariances, changes through time. But, it was not until the introduction of what is now known as *Modern Financial Econometrics* that applied researchers in financial and monetary economies started explicitly modelling variation over time in second-order moment. To that end, in his seminal paper in 1982, Engle introduced the autoregressive conditional heteroscedastic (ARCH) model which allows the conditional variance to change overtime as a function of past errors keeping the unconditional variance constant. It has been observed that this model captures many empirically observed temporal behaviours like the thick tail distribution and volatility clustering of many economic and financial variables (see, Bollerslev *et al.*, (1992), Bera and Higgins (1993), Bollerslev *et al.*, (1994), Shephard (1996) and Gourieroux (1997), for excellent surveys on ARCH/GARCH models and its various generalizations). Subsequently, this model was generalized by Bollerslev (1986), and this is called the generalized autoregressive conditional heteroscedasticity (GARCH) model.

One important point to be noted while studying the risk-return relationship is that, as the degree of uncertainty in asset returns varies over time, the compensation required by risk-averse investors for holding these assets must not only be time-varying but also be such that investors are rewarded for taking additional risk by ensuring a higher expected return. One way to operationalise this concept is to let the return be partially determined by its time-varying risk. To this end, Engle *et al.*, (1987) introduced the ARCH-in-mean (ARCH-M) model where the conditional variance of asset returns enters into the conditional mean equation explicitly. In this model, therefore, the changing conditional variance directly affects the expected return on a portfolio, and the risk-return relationship is expected to be positive since increase in risk given by an increase in conditional variance is likely to lead to a rise in the mean return. After the publication of the paper by Engle *et al.*, (1987), it was noted that this relationship supports the theoretical finance model like the CAPM. For instance, French, Schwert and Stambaugh (1987) and Campbell and Hentschel (1992) have found that the relationship is positive.

It may, however, be noted that in some empirical studies (see, Turner *et al.*, (1989), Nelson (1991), and Glosten *et al.*, (1993)), the risk-return relationship has been found to be in the contrary i.e., increased risk has lead to a decrease in expected return. In finance literature, this has been attributed to what is called 'volatility feedback hypothesis' which relies on the existence of time-varying risk premium as the link between change in volatility and returns. In fact, this hypothesis states that any shock in volatility will cause change in returns to be negative. A large number of researchers including Pindyck (1984), French *et al.*, (1987), Turner *et al.*, (1989), Champbell and Hentschel (1992), Bekaert and Wu (2000), Wu (2001), Kim *et al.*, (2004), and Mayfield (2004) have found evidence in support of this hypothesis.

An important limitation of the class of ARCH/GARCH models is that they impose a symmetric response of volatility to positive and negative shocks. This arises since the conditional variance is a function of the squared lag residuals. However, it has been argued that a negative shock to financial time series is likely to cause volatility to rise by more than a positive shock of the same magnitude. In case of equity/stock returns, such asymmetric responses are attributed to 'leverage effect', and empirical evidence in favour of this asymmetry in conditional variance of stock returns is numerous. Insofar as models capturing asymmetry in volatility is concerned, two popular asymmetric formulations are available - one due to Nelson (1991), called the exponential GARCH (EGARCH) model, and the other due to Glosten *et al.*, (1993), called the GJR model. A large number of empirical studies on returns have been done with these two asymmetric models and both have been found to be very useful. To cite a few, Pagan and Schwert (1990), Lee (1991), Cao and Tsay (1992), and Heynen and Kat (1994) found the EGARCH model for volatility of stock indices to perform well while, on the other hand, Brailsford and Faff (1996), and Taylor (2004) found GJR-GARCH to outperform GARCH in stock indices. In general, models that allow for volatility asymmetry were also found to perform well in the forecasting context because of the strong negative relationship between volatility and shocks. Consequently, the simple GARCH-in-mean model where the conditional variance is symmetric GARCH has been found to be not quite appropriate and adequate, especially in case of equity/stock returns. Appiah-Kusi and Menyah (2003) and Kulp-Tåg (2007) have considered the modelling framework of EGARCH-in-mean (EGARCH-M) to find to what extent the relation improves by incorporating leverage effect.

During the last three decades, nonlinear time series models have become popular for analysing many economic and financial time series. However, since the seminal work by Engle (1982), where nonlinear dependence refers to second-order dependence only, other nonlinear models for conditional variance being applied are the threshold ARCH/GARCH model by Zakoian (1994), Rabemananjara and Zakoian

(1993), the volatility switching GARCH by Fornari and Mele (1997), and the smooth transition GARCH by Gonzalez-Rivera (1998). Higgins and Bera (1992) introduced the nonlinear ARCH (NARCH) model which encompasses various functional forms for the conditional variance. Their model also provides a framework for testing the further nonlinearity in the ARCH model. Ding *et al.*, (1993) presented the asymmetric power ARCH (PARCH) model which is characterized by a large degree of flexibility. In fact, the ARCH, GARCH, NARCH, GJR and TGATCH models are special cases of the PARCH model.

Hegerud (1996) introduced two smooth transition ARCH models where he considered two transition functions *viz.*, logistic and exponential. Here the nonlinearity is considered only in the conditional variance equation. In both these models, asymmetry regarding the sign of the error term is considered. Further, Gonzalez-Rivera (1998) developed a smooth transition GARCH (ST-GARCH) model where asymmetry in the variance response is modelled by the smooth transition mechanism. A distinct advantage of this model is that threshold type GARCH models are nested in this model.

It is worthwhile note that the literature on the modelling conditional variance along with other statistical issues involved have grown enormously while the same for conditional mean is rather limited. It is also a fact that from statistical consideration, model for conditional mean should be correctly specified so that misspecification in the conditional variance is avoided. Researchers often model time series without paying careful attention to the behaviour of the first moment, i.e., conditional mean, and only concentrate on the second moment i.e., conditional variance. There have been some works recently to deal with this issue appropriately. Thus, we find that models which take into account appropriate specifications (linear as well as nonlinear) for both conditional mean and conditional variance are being proposed. For instance, Li and Li (1996) used a double-threshold ARCH (DTARCH) model where both mean and variance have threshold structures. This model is rather flexible since many other models are included in this model as special cases. The results from empirical work employing this model indicate that asymmetry in both mean and variance is often statistically significant, and hence, these asymmetries should be accounted for when modelling financial data.

Lundbergh and Terasvirta (1998) used a smooth transition autoregressive model for the mean and a smooth transition GARCH model, which is a generalization of the GJR GARCH model, for the conditional variance. This model has been found to be good for characterizing high-frequency time series data. Koutmos (1998) used an asymmetric autoregressive threshold GARCH (asAR-TGARCH) model which also incorporates the nonlinearity in both mean and variance. The results from this model show that the conditional mean and conditional variance of the stock returns are asymmetric, and that negative returns reverted more quickly than positive returns.

Recently, Nam *et al.*, (2001 and 2002), Nam (2003), and Nam *et al.*, (2003) have used an asymmetric nonlinear smooth transition GARCH (ANST-GARCH) to investigate the uneven mean reverting pattern of monthly returns, and their works provide empirical support to what is called the 'market over reaction hypothesis' of stock markets. Brannas and De Gooijer (2004) have combined an asymmetric moving average model for the mean with an asymmetric quadratic GARCH for the variance equation. This model allows the response to shock to behave asymmetrically. Kulp-Tåg (2007) has introduced an asymmetric nonlinear autoregressive model for the conditional mean and the EGARCH model for the conditional variance to capture the asymmetric nature of stock returns, and considered his study in the framework of 'conditional variance-in-mean' to find the risk-return relationship.

The issue of whether stock returns are influenced by market movements/conditions or not, has drawn attention rather recently. Of course, the phenomenon of market conditions as understood by bull and bear markets, is a widely discussed topic in finance literature. Although, as discussed in Candelon *et al.*, (2008), there is no consensus in the academic literature on determining the bull and bear market turning points. These two market situations are treated as cyclical features and considered to be broad market movements that can be illustrated with low frequency data. Some references to literature on bull and bear markets are Turner *et al.*, (1989), Perez-Quiros and Timmermann (2000 and 2001), Ang and Bekaert (2002), and Coakley and Fuertes (2006). It is interesting to note that apart from parametric methods, nonparametric methods are also being used to identify such market conditions as well as recessions and booms in stock markets (see, in this context, Maheu and McCurdy (2000), and Candelon *et al.*, (2008)).

In the context of risk-return relationship, Levy (1974) suggested that separate risk-return relationships for different market conditions are to be considered. Fabozzi and Francis (1977) were the first to formally estimate and test the stability of market betas of the CAPM over bull and bear markets. Using monthly returns on NYSE stocks and S&P 500, and applying simple econometric tools, they found no evidence to support that these two stock markets have an asymmetric effect on beta. Extending this study by defining bull and bear markets using a threshold model, Kim and Zumwalt (1979) found no evidence to support the beta instability. But they concluded that investors require a premium for taking downside risk and pay a premium for upside variation. In the context of finance literature, in general, it has long been investigated whether or not the asymmetric risk or beta of the CAPM responds asymmetrically to good and bad news as measured by positive and negative returns, respectively. Generally speaking, there are some studies which have examined the validity of the asset pricing models, especially the CAPM, taking into account different market movements, defined as 'good', 'bad', 'up' and 'down' markets. Some of these references are: Bharadwaj and Brooks (1993), Pettengil, *et al.*, (1995), Howton and Peterson (1998), Crombez and Vandetr Vennet (2000), Faff (2001), and Granger and Silvapulle (2002). Except for Granger and Silvapulle (2002), all other studies are with return data at low (monthly) frequency. Using daily return data, Granger and Silvapulle (2002) investigated the asymmetric response of beta to different market conditions by modelling the mean and the volatility of CAPM as nonlinear threshold models with three regimes. Finally, Galagedera and Faff (2005) carried out a study where they investigated whether the risk-return relationship varies, depending on changing market volatility and up-down market conditions.

1.2.2 Multivariate analysis of returns

In this section, we review briefly the literature on multivariate GARCH (MGARCH) model and its extensions, especially with reference to risk-return relationship in the multivariate set-up (see, Bawens *et al.* (2006), for an excellent survey on MGARCH model and its various extensions and generalizations). Understanding and predicting volatilities and correlations of asset returns has been the object of much attention, since volatilities and correlations are the two most important elements in financial activities such as asset pricing, asset allocation decision, portfolio management and risk assessment.

Although univariate ARCH/GARCH model and its important extensions are very powerful in explaining the stylized facts of financial assets, researchers have found them unsatisfactory and not very useful in examining the characteristics of two or more financial assets simultaneously. In reality, often, we are more concerned about the relationship between volatilities of several stock markets or assets, especially because of increasing connectedness across financial markets. In the context of stock markets, studying the transmission of stock returns for a set of markets has become important evidence of spillover, and volatility transmission from one market to another market is also now quite well-established (see, for example, Engle *et al.* (1990), Hamao *et al.* (1990), and Martens and poons (2001)). Recognizing these important features, modelling volatilities of financial assets in multivariate set-up gained importance since the late 1980's. There are basically two directions for modelling multivariate time series: (*i*) modelling the variance covariance matrix directly, and (*ii*) modelling the correlation between the time series. Bollerslev *et al.* (1988) proposed the first multivariate GARCH model for the conditional variance-covariance matrix, H_t, which is called the VEC model, where each element of H_t

is a linear function of the lagged squared errors and cross-products of errors and lagged values of the elements of H_t. It should be noted that the advantage of this model is that we can directly interpret the coefficients in the model. However, this model is a very general model and it is very difficult to apply in practice since the number of parameters involved in this model is very large and it is difficult to ensure the positive definiteness property of H_t. To overcome these problems, Bollerslev *et al.*, (1988) introduced a simplified version of the VEC model, i.e., the diagonal VEC model. This model reduces the number of parameters greatly and it is relatively easier to derive the conditions on the parameters to guarantee the positive definiteness of H_t.

Engle and Kroner (1995) proposed the BEKK model (an acronym used for the synthesized work on multivariate model of Baba, Engle, Kraft and Kroner) which can be viewed as a restricted version of the VEC model. The BEKK model has the good property, *viz.*, that the conditional variance-covariance matrix is positive definite by construction. But the number of parameters in the BEKK model is still quite large.To deal with this problem, other simplified models including the diagonal BEKK model and the scalar BEKK model have been proposed, but these are too restrictive as both impose the same dynamics to all the variances and covariances. Some other related models in this category are the flexible MGARCH, factor GARCH (due to Engle *et al.*, (1990)), orthogonal GARCH model and latent factor model.

Another important direction in which the MGARCH model has grown involves modelling the correlations between the series indirectly instead of modelling the conditional variance-covariance matrix directly as in the case of the BEKK model. Bollerslev (1990) first introduced a class of constant conditional correlation (CCC) model in which conditional correlation matrix is assumed to be constant, and thus the conditional covariances are proportional to the product of the corresponding conditional standard deviations. He and Terasvirta (2002) have used a VEC-type formulation for the conditional variances to allow for interactions between conditional variances. They called this the extended CCC model. Using daily data from 1994 to 1998, Kasch-Haroutounian and price (2001) investigated the interdependences among four central European stock markets (Czech Republic, Poland, Hungary and Slovakia) employing two different multivariate GARCH approaches - the constant conditional correlation (CCC) model and the BEKK GARCH model. Using the CCC model, the authors have found positive and statistically significant conditional correlation coefficients between Czech and Hungarian stock markets as well as between Hungarian and Polish stock markets. For the other combinations, values of conditional correlation were found to be very low and statistically insignificant. Scheicher

(2001) examined the comovements between three European emerging markets *viz.*, the Czech Republic, Poland and Hungary, during 1995 -1997, using vector autoregression-CCC (VAR-CCC) model. His results indicate the presence of both regional and global spillovers in returns, but only regional spillovers in volatilities. These results suggest that global shocks are transmitted to the central European stock market through returns rather than through volatility shocks. Using the CCC and the smooth transition conditional correlation (STCC) models, Savva and Aslanidis (2010) investigated the stock market integration both among five Central and Eastern European (CEE) countries (Czech Republic, Poland, Hungary, Slovakia, Slovenia) and *vis-a-vis* the aggregate Euro area markets in 1997-2008. The largest CEE markets *viz.*, the Czech Republic, Poland and Hungary, exhibit higher correlations *vis-a-vis* the Euro area as compared to Slovakia and Slovenia. The specification of the CCC model is innovative because it has desirably fewer parameters, it saves a lot of computational cost as one correlation matrix is needed to be inverted in each iteration using the maximum likelihood method, and it automatically guarantees the positive definiteness of the variance-covariance matrix. But the assumption that conditional correlation matrix is time-invariant is unrealistic in many empirical applications. In fact, it is now well established that correlations of stock returns are not constant through time. Correlations tend to rise with economic or equity market integration (see, for instance, Erb *et al.* (1994), Longin and Solnik (1995), and Goetznmann *et al.* (2005)).

Tse and Tsui (2002), and Engle (2002) generalized the CCC model to make the conditional correlation matrix time-varying. An additional difficulty for the time-varying conditional correlation model is that the time-varying conditional correlation matrix has to be positive definite for every t. The dynamic conditional correlation (DCC) model proposed by Engle (2002), specifies a GARCH-type dynamic matrix process and then transform the variance-covariance matrix to the correlation matrix. Alternatively, time-varying correlation (TVC) model of Tse and Tsui (2002) formulated the conditional correlation matrix as a weighted sum of past correlations, where the conditional correlation matrix was assumed to resemble that of an ARMA structure. However, both models of Engle (2002), and Tse and Tsui (2002) lose computational efficiency since the number of correlation matrices needed to be inverted in each iteration using the maximum likelihood method is the same as the number of observations. Another drawback of the DCC-type models is that it restricts all the correlation processes to obey the same dynamic structure. Interestingly, these models can be estimated consistently using two-step estimation.

Of late, the DCC model is being used increasingly, especially in studies on contagion effects. For instance, Naoui *et al.* (2010) have tested the existence of contagion phenomenon following the US sub-prime crisis for six developed and ten emerging stock markets. They have concluded that contagion is strong between the US and the developed and emerging countries during the sub-prime crisis. Hwang *et al.* (2011) have examined the contagion effect of the US sub-prime crisis on international stock markets using a DCC model on return data of 38 countries. In conclusion, they have found evidence of financial contagion not only in emerging markets but also in developed markets during the US sub-prime crisis. Bouaziz *et al.* (2012) have tested the contagion effect of the US stock market on the stock markets of developed countries during the sub-prime financial crisis (2007-2008) by using the same model. They have found that correlations between markets have significantly increased during the US sub-prime crisis period and accordingly concluded that the crisis has spread across different markets which is a clear evidence of contagion. Very recently, Lean and Teng (2013) have employed the DCC model and presented the trend in degree of financial integration in a time-varying manner. Wang and Moore (2008) have used this model and examined the interdependences between three major emerging markets (the Czech Republic, Poland and Hungary) *vis-a-vis* the aggregate Euro area market. They have found that the financial crisis and the EU enlargement have substantially increased the correlations between Central and Eastern European countries and the Euro area markets. Lanza *et al.* (2006), and Manera *et al.* (2006) examined correlation and volatility in the oil forward and future markets. Edwards and Susmel (2001), and Edwards and Susmel (2003) investigated the volatility dependence and contagion in equity and interest rate in emerging markets. Balasubramanyan and Susmel (2004) provided the evidence of volatility comovements and spillover from Asian markets. Yang (2005) used a DCC analysis to examine the role of Japan on the four Asian markets and found that stock market correlations fluctuate widely over time and volatilities are contagious across markets. Some other references, in this literature, are: Andersen *et al.* (2006), Kuper and Lestano (2007), Wang and Thi (2007), Arouri *et al.* (2010), Asai (2013), Celik (2012), Pesaran and Pesaran (2010), Lyocsa *et al.* (2012), Amhad *et al.*(2013), and Gjika and Horvath (2013).

Several variants of the DCC model are recently being proposed in the literature. For instance, Billio *et al.* (2003) argued that constraining the dynamics of the conditional correlation matrix to be the same for all the correlations is not appealing. To overcome this, they proposed a block diagonal structure where the dynamics is constrained to be the same only within each block. However, the number of blocks has to be defined *a priori*, which may be tricky in some applications. Pelletier (2006) proposed a regime switching DCC model where the conditional correlations follow a switching regime and the correlation matrix is constant in each regime but may vary across regimes. This model is highly computation intensive. Cappiello *et al.* (2006) advocated the asymmetric generalized dynamic conditional correlation (AG-DCC) model. The AG-DCC model process allows for series-specific news impact and smoothing parameters and permits conditional asymmetry in correlation dynamics. The AG-DCC specification is well suited to examine the correlation dynamics among different asset classes, and it investigates the presence of asymmetric response in conditional variances and correlations. In consideration to include the asymmetric effect and to avoid the same dynamics for all assets in financial time series, Vargas (2008) proposed the asymmetric block dynamic conditional correlation (ABDCC) model. McAleer *et al.* (2008) have suggested a generalized autoregressive conditional correlation model. Finally, Engle and Kelly (2012) have developed the equicorrelation model which is a highly simplified version of the DCC model. However, the equicorrelation assumption seems to be very restrictive and inadequate.

1.3 Stock Returns and Monetary Policy

During the last three decades, there has been a steady increase in studies investigating if monetary policy affects stock markets. Central bank uses many monetary policy instruments including open market operations, changes in reserve requirements, discount rate, the interest rate of inter-bank, and overnight lending of reserves to manipulate the money supply and interest rate which, in turn, affects the overall economy. Way back in 1974, Rozeff explained that as claims on real assets and common stocks are affected by unexpected changes in monetary policy since unexpected changes in monetary policy contain unexpected information which have not been reflected in current stock prices. In contrast, as latest as in 2009, Mishkin has suggested that monetary policy might negatively affect stock prices because monetary policy can alter the path of expected dividends, the discount rate or the equity premium.

However, despite the accumulation of papers, whether monetary policy affects stock markets or not is still a critical issue in modern finance. Black (1987) argued that monetary policy cannot affect stock returns and Smith and Goodhart (1985) found no empirical evidence of the impact of monetary policy on stock returns (see, for relevant details, Black (1987), McDonald and Torrance (1987), and Tarhan (1995)). However, many studies have provided evidence of significant negative responses of stock returns to monetary policy announcements, (see, for instance, Waud (1970) and Bredin *et al.* (2007)). A number of studies including those by Pearce and Roley (1983, 1985), Jensen and Johnson (1993, 1995, 1997) and Wongswan (2006), have shown that the level of stock return significantly responds to the monetary policy announcements. However, Hafer (1986), and Hardouvelis (1987) showed that the responses vary i.e., responses could be either significantly negative or insignificant, depending on sample periods. Using money aggregate data as a measure of money supply, some empirical studies in the 1970's such as Homa and Jafee (1971), Keran (1971), and Hamburner and Kochin (1972) found that stock returns lag behind changes in monetary policy. In contrast, Cooper (1974), Pesando (1974), Rogalski and Vinso (1977) showed that there is no significant forecasting power of past changes in money.

Ever since the seminal paper by Bernanke and Blinder (1992), the federal fund rate has been the most widely used measure of monetary policy. As such, the relationship between monetary policy and stock returns has been re-examined by using the instruments of interest rate in the financial literature. Thorbecke (1997) and Patelis (1997) demonstrated that shifts in monetary policy help to explain US stock returns. Conover, Jensen and Johnson (1999) showed that foreign stock returns generally react both to local and US monetary policy.

Two important contributions to the literature on the effects of monetary policy on the stock market have been made recently. The first one emphasizes on the role of financial markets' expectations about the future course of monetary policy. Bernanke and Kuttner (2005) have extracted unanticipated monetary policy from Federal funds futures and found the monetary policy to have, surprisingly, a significant effect on equity prices through changes in the equity premium. The second one has focused on the prospect of endogeneity. Regobon and Sack (2003) have shown that the causality between interest rate and stock prices may run in both directions. After accounting for this endogeneity, they have found a significant monetary policy response to the stock markets. Of course, there are some studies that report mixed results, say, for instance, Hafer (1986), and Hardouvelis (1987). Similarly, while some studies have shown that monetary policy announcements have no effect on stock market volatility (e.g., Rangel (2006)), some others have found that there is indeed evidence of that effect (e.g., Lobo (2000), Bomfim (2003), and Chang (2008)).

Finally, cyclical variation in stock returns has been widely reported in the literature. Particularly, bull and bear markets have been explicitly identified in Maheu and McCurdy (2000), Pagan and Sossounov (2003), Edwards *et al.*, (2003) and Lunde and Timmermann (2004). Also, the class of models where there exists agency cost of financial intermediation (financial constraint), asserts that when there is informational asymmetry in the financial market, agents behave as if they are constrained financially. Moreover, as Bernanke and Gertler (1989), and Kiyotaki and Moore (1997) have noted, financial constraint is more likely to bind in bear markets, and hence, a monetary policy may have greater impacts in bear market situation.

1.4 Motivation

Since the middle of 1980s, time series modelling of returns is carried out specifying models for both the conditional mean and conditional variance of returns. However, till 1987, there was no model in the literature where conditional variance was allowed to affect returns through the conditional mean directly. Although it is reasonable to expect that the conditional mean and conditional variance of returns should have an explicit relationship so that the direct effect of risk on returns could be captured and studied. Such a model, known as the ARCH-in-mean (ARCH-M) model, was first introduced by Engle, Lilian and Robbins in 1987 and since then it has become a workhorse in the time-varying risk premium literature. As it is, there is a large body of empirical work with return data, where several generalizations and extensions of the original (G)ARCH-M model, like the EGARCH-M, threshold GARCH-M (TGARCH-M), smooth transition GARCH-M (STGARCH-M), have been applied. Also, there are few studies where the different states of stock market based on returns, especially the bull and bear markets, have been modelled along with symmetric and asymmetric conditional variance.

But all these studies have used returns at monthly frequency. In fact, as noted by Gonzalez et al. (2006), bull and bear markets are considered to be broad market movements that can be illustrated using low frequency data. However, there are practically no empirical studies with returns at daily frequency with similar consideration to specifications of conditional mean and variance in the framework of 'volatility-in- mean' model where the risk aversion parameter is assumed to be different for different market movements. Such a study would establish whether or not the direct effect of time-varying risk, as captured through the relative risk aversion parameter, responds differently to different states of stock market. This thesis is thus primarily motivated by this important issue of risk being different for different market situations and that too in a modelling framework where risk is allowed to affect the conditional returns directly. This can be studied both at univariate and multivariate levels. At the univariate level, the question primarily being asked is: Is the effect of risk on stock returns different in up and down markets?

It is well known that such studies at univariate level has certain limitations when several stock markets are being considered together. Studies in multivariate framework entail links across several stock markets. Empirical modelling of such links is relevant for trading and hedging strategies and these links provide insights into the transmission of shocks (news) across stock markets of different countries. Further, it helps to study the spillovers from one stock market to another in mean return and volatility along with cross market linkages. It is now widely accepted that financial volatilities move together over time across assets and markets. Recognizing this feature through a multivariate modelling framework leads to more relevant empirical models than working with separate univariate models. In the context of stock markets, the most obvious application of the multivariate GARCH (MARCH) model is the study of relationship between the volatilities and co-volatilities of several stock markets. In fact, issues like volatility of returns of one stock market getting transmitted to another stock market directly (through its conditional variance) and/or indirectly (through its conditional covariances) can be studied directly by application of the MGARCH model, and this involves specifications of the dynamics of covariances and correlations.

To this end, there are quite a few specifications of the MGARCH model based on different specifications, and the most widely used ones are the BEKK and dynamic conditional correlation (DCC) models. The BEKK model captures the dynamics of variances and covariances, but it is not very suitable if volatility transmission is the main object of interest. On the other hand, the DCC model generalizes the constant conditional correlation (CCC) model by removing the assumption of constancy of conditional correlation since it is very unrealistic in many situations. The DCC model involves parameters which directly capture the volatility transmission, and it also allows for different kinds of persistence between variances and correlations.

The literature on capturing leverage effect through extensions of MGARCH model is extremely limited. In case of multivariate series, the arguments on leverage effect run as follows: the variances and covariances react differently to a positive than to a negative shock. A model that takes explicitly the signs of errors into account is the asymmetric dynamic covariance (ADC) model which nests some natural extensions of the MGARCH model incorporating the leverage effect. There is also a generalization of the univariate GJR specification in case of bivariate BEKK model. Insofar as extension of MGARCH model volatility-in- mean framework is concerned, there are very few studies. One distinct advantage of MGARCH-M model is that apart from the spillovers in the mean and variance of returns, cross-market GARCH-in-mean effects can also be studied through this model. Although with the advances in econometric modelling, interdependences in terms of both first and second order moments of return distributions are being studied, yet, in the multivariate context, extension of the MGARCH model where asymmetry in conditional variance is considered and also the MGARCH-M model where conditional variance directly affects the conditional mean, have been studied in a limited way. The relative dearth of such studies at multivariate level, especially where the effect of risk on expected return is allowed to be different for different market conditions, has also been one of the motivations for this work.

Stock market is an important channel of monetary policy that can be used to influence real economic activities. Real economic activities are affected by stock markets through a number of channels such as wealth effect of stock prices on consumption and economic growth. Hence, it has been of great interest to both the financial economists and macroeconomists to study whether monetary policy affects stock returns or not. A number of empirical studies have been done on this problem, but the findings are mixed in nature. Hence, a natural question that arises is: Is the finding of insignificant/significant role of changes in money supply is due to some inadequacies in the modelling approach and assumptions as well as in the choice of the instruments for monetary policy? Furthermore, cyclical variation, particularly bull and bear situations in stock markets, is a widely reported phenomenon in every stock exchange, and hence another question that arises is: Does a monetary policy have different (asymmetric) effects on stock returns in bull and bear markets? Chen (2005) has investigated these two questions with S&P 500 using a modified version of the Markov regime switching regression developed by Hamilton (1989) in two different perspectives – fixed transition probability and time varying transition probability, the latter allowing switches between the two markets states to depend on monetary policy.

Basically, the purpose of such studies is to empirically investigate if monetary policy has different effects on stock returns characterized by two market conditions. Although the primary focus of this thesis, as already stated, is to find if the effects of risk on different market movements are different, we are also examining the relationship concerning the effect of monetary policy on returns. In fact, as Gust and Lopez-Salido (2009) have argued, unanticipated changes in monetary policy affect equity prices primarily through changes in risk. Further, Bekaert, Hoerova and Duca (2013) have also shown that implied volatility of stock market strongly co-moves with the monetary policy. To the best of our knowledge, such studies have not been carried out for other developed stock markets and important emerging economies. The findings of such a study involving two groups of countries from their status of development, should be very interesting, especially because monetary policy is extremely important in influencing stock returns. And this is indeed the last motivation for this work.

1.5 Format of the Thesis

The other chapters of the thesis are organized as follows:

Chapter 2: Data: Some Important Characteristics

In this chapter, we primarily discuss about the data sets of all the eight stock markets used in this study. Apart from the usual summary statistics, the important characteristics like stationarity, autocorrelation (both linear and squared dependences), and existence of structural breaks in the time series have also been studied. The organization of the chapter is as follows. It begins with an introduction in Section 2.1. In Section 2.2, choice of the stock markets has been discussed. Thereafter, in the next section, plots, nature of the data and summary statistics like the mean, standard deviation, skewness and kurtosis of all the time series are presented. In Section 2.3, some important characteristics of all the time series *viz.*, stationarity (linear) autocorrelations, squared autocorrelations and structural breaks are discussed, based on application of appropriate tests. This chapter has been concluded with some remarks in Section 2.5.

Chapter 3: Risk-Return Relationship in EGARCH-in-Mean Framework Under Up and Down Market Movements

In this chapter, it is empirically investigated whether or not risk associated with a stock market responds differently in two different states of the stock markets - up and down - at the univariate level. This is done in the framework of 'volatility-in-mean' where volatility is being taken to be asymmetric in nature. The format of this chapter is as follows: Section 3.1 gives the introduction of this chapter. In Section 3.2, the proposed models are introduced. The estimation results are discussed in Section 3.3. Inferences based on statistical tests are presented in the next section. The paper ends with some concluding remarks in Section 3.5.

Chapter 4: Threshold VAR - Bivariate Threshold GARCH-in-Mean Model: The BEKK Approach

This chapter studies the inter-relationships, in terms of return and volatility spillovers as well as GARCH-in-Mean spillovers between different stock markets using daily returns data in bivariate GARCH-in-mean framework. In this framework, the model for the conditional mean has been specified from consideration of the two different market situations *viz.*, up and down, along with different – both symmetric and asymmetric – specifications for the conditional variance. Of the two basic models for the conditional variance-covariance matrix, the BEKK and the dynamic conditional correlation (DCC), the first one has been applied here . Several hypothesis of interest have also been tested by using the LR and the Wald tests.

The chapter is organized as follows. Introduction is given in Section 4.1. The proposed model along with some existing models are presented in the next section. Section 4.3 outlines the estimation and tests of hypotheses. In Section 4.4, the empirical results on estimation of the models are discussed. The findings on the tests of hypotheses are presented in Section 4.5. This chapter ends with some concluding remarks in Section 4.6.

Chapter 5: Smooth Transition VAR - Bivariate Threshold GARCH-in-Mean Model: The DCC Approach

This chapter deals with the same problem as in Chapter 4 using basically the same modelling framework. The main difference, however, lies in the approach used in dealing with this problem in the bivariate case. In other words, unlike the BEKK approach in the preceding chapter, the DCC approach is applied here. The organization of this chapter is as follows. In Section 5.1, the introduction to this chapter is presented. In the next section, we discuss about the models and methodology used in this chapter, The empirical results are discussed in Section 5.3. This chapter closes with some concluding observations in Section 5.4.

Chapter 6: Effects of Monetary Policy on Stock Returns Under Up and Down Markets: The Markov Switching Regression Model

In this chapter, instead of the effects of risk, the effects of monetary policy, on stock returns under up and down markets are studied. This is done by using two models, *viz.,* (*i*) the Markov regime switching with fixed transition probability and (*ii*) the Markov regime switching with time varying transition probability. In the second model, the switch over between the two market conditions is assumed to depend on monetary policy . Growth rate of money supply and the change in discount rate are the two instruments of monetary policy used in this work.

The format of the chapter is as follows. Introduction is given in Section 6.1. Section 6.2 presents the methodology used in this work. Data sets are stated in Section 6.3. Empirical analysis is carried out in Section 6.4. Concluding remarks are made in Section 6.5.

Chapter 7: Summary and Future Ideas

The last chapter of this thesis begin with a brief introduction to the problem studied in this thesis. In the next section i.e., in Section 7.2 , a summary of the major findings of the entire work are presented. The concluding section contains a few ideas for further work in this area.

Chapter 2

Data: Some Important Characteristics

2.1 Introduction

The empirical study done in this thesis involves time series of stock indices of a number of countries. In the next three chapters i.e., Chapters 3, 4, and 5, return data at daily frequency are used. In Chapter 6, apart from returns, data on two instruments of monetary policy *viz.*, money supply and interest rate are required. Since data for the latter variables are not available at a frequency higher than monthly, time series data on all the three variables have been used at monthly frequency in the computations carried out in Chapter 6.

Since the study is a multi-country one, we have chosen eight countries - four each from advanced economies and important emerging economies. Specifically, we have taken the US, the UK, Hong Kong and Japan for the former, and Brazil, Russia, India and China, which constitute the BRIC group of countries, for the latter. In this chapter, we first state, in Section 2.2, why stock markets of these countries have been chosen for this study. Thereafter, in the next section, plots, nature of the data and summary statistics like the mean, standard deviation, skewness and kurtosis of all the time series are presented. In Section 2.3, some important characteristics of all the time series *viz.*, stationarity (linear) autocorrelations, squared autocorrelations and structural breaks are discussed, based on application of appropriate tests. This chapter has been concluded with some remarks in Section 2.5.

2.2 Choice of Stock Markets

The choice of the eight stock markets has been made keeping in mind the fact that characteristics of the stock markets under study may vary across developed and important emerging economies since in the latter category the growth is substantially increasing in nature, and with increasing openness of these markets these are getting rapidly integrated with the stock markets of advanced countries. At the same time, it is also worth noting that because of various reasons including possibly the stability of major macro variables, financial crises of the recent past in the western economies, especially in the USA, didn't have much effect on the BRIC countries. It is now well understood that both the developed and emerging markets move together over the short run. There are several studies which have looked into such links. For instance, Cha and Cheung (1998), and Janakiramanan and Lamba (1998) examined the linkage between Asia-Pacific equity markets and the US stock market, and established that the US has a significance influence on these markets in addition to a number of interrelationships within the Asia-Pacific region. Not only that such studies have established spillovers in mean relationships between markets, there has been significant research (see for instance, Engle *et al.* (1990) and Hamao *et al.* (1990)) examining the presence of volatility spillovers across these markets.

More recent studies on financial crises and contagion effects provide further evidence that there is significant transmission across markets between developed and emerging economies as well as among members of each such group of countries. For instance, the works of Kaminsky and Reinhart (1998) and Bai *et al.* (2003) have documented that mean and volatility spillovers occur between asset markets suggesting that events in one market can be transmitted to the other and that the magnitude of such interrelationship may be strengthen during crisis periods. Such linkages from Japan and the US to the Pacific Basin region have also been found by Ng (2000). Worthington and Higgs (2004) have also provided transmission of returns and volatility among nine developed and emerging Asia Pacific markets. Thus, the existing empirical studies show that with increasing financial liberalization as well as changes in rules and regulations governing stock market operations, emerging and other blocks of countries also try to develop stock markets like those for advanced countries so that the stock markets are well structured having, *inter alia.*, strong regulatory authority as well as well-established trading rules. This has made increasing integration between developed economies and important emerging economies as a fact of reality. Keeping all these in mind, we have chosen stock markets of four developed economies - the US, the UK, Hong Kong[1], and Japan, and stock markets of BRIC countries under emerging economies

[1]Despite being a highly developed economy and globally an important economic power, there are not many studies

- Brazil, Russia, India, and China - for our study.

At this stage, it may be worthwhile to state some facts and figures about the BRIC countries which would indicate their growing importance and justify their choice for this study. The BRIC group of countries consisting of Brazil, Russia, India, and China, have common features like large land area, huge population and rapid economic growth. In 2010, these countries together accounted for over a quarter of the world's land area and more than 40% of world's population. The acronym, BRIC, coined by O'Neil in 2001 intended to signify the likely shift in global economic power away from the developed G7 economies towards the developing world. Thus the sample period of this study covers almost the entire period of BRIC's existence, and to that extent, inclusion of this group of countries in this study should be interesting and useful. These four countries have been accepted as the fastest growing "emerging markets" since early 2000s. In 2000, the share of this four developing countries in global GDP in terms of purchasing power parity (PPP) was 16.4%, but in 2010 this figure raised to 25%. The main contribution was due to China and India, whose shares increased from 7.2% to 13.3% and 3.6% to 5.3%, respectively, in the above-mentioned decade. The share of this group in world trade has also improved significantly during the last two decades – from 3.6% to over 15%. Although the largest increase in terms of value has been in case of China – from less than 2% to over 9% – others too have made significant progress. Brazil's share has risen from 0.8% to 1.2% while those of Russia and India from 1.5% to 2.3%, and 0.5% to 1.8%, respectively. According to an estimate by Goldman Sachs, the four original BRIC countries are expected to represent 47 per cent of global GDP by 2050, which would dramatically change the list of the world's 10 largest economies.

BRIC markets have also become attractive destinations for FDI. FDI inflows in BRIC have increased at nearly 10% over a ten-year period – from nearly \$80 billion in 2000 to over \$220 billion in 2010. The trend of FDI outflows is also similar to that of inflows. FDI outflows from the BRIC economies have increased over 35% in the last decade. These figures establish the fact that BRIC economies are not only major destinations for FDI, but these are also playing an increasingly important role in meeting global demands for capital. As regards the performance of the stock markets in BRIC, there has been marked and significant improvement during the first decade of its existence. A significant rise in equity indices was observed between the years 2000 and 2008. During this period, the price-earning ratio as

using such nonlinear models with returns on Hong Kong stock market index. It is because of this reason that we have included Hong Kong in our study. The importance of this stock market can be understood by noting that the total market capitalization of the listed companies in Hong Kong stock market was US\$ 1162 billion in 2008. Further, this stock market is now the second and sixth largest stock market in Asia and in the world, respectively an indicator of capital markets has been relatively stable. The strength of the stock markets measured in terms of market capitalization to GDP of BRIC economies progressively deepened over the years. Combined external financing of capital markets in BRIC from bonds, equities and loans (in absolute term) also increased significantly during this period.

There is also a distinctive advantage of such multi-country studies in that these are based on the same model methodologies, time periods and data frequency. Further, the investors sentiment and reactions are also likely to be somewhat different in different market conditions, and this is likely to lead to some differences in the models for returns on the stock markets of these two groups of countries - developed and emerging.

2.3 Data, Plots and Summary Statistics

In all these eight countries, more than one stock index are available. However, we have taken only one index for each country. Accordingly, the stock indices considered are, S&P 500 (the US), FTSE ALL (the UK), HANG SENG (Hong Kong), NIKKEI 225 (Japan), BOVESPA (Brazil), MICEX (Russia), SENSEX (India) and SSE COMPOSITE (China). The time series of all these time series at daily frequency have been downloaded from the official website of Yahoo Finance (http://finance.yahoo.com/) and Bombay Stock Exchange (http://www.bseindia.com/) . The time period considered for this study is 01 January 2000 to 31 December 2012 for all the series. The total number of observations are not the same for all the eight series simply because of varying number of holidays in different countries when stock market remain closed. Thus, we note that SSECOMPOSITE of China has the highest number of observations (3329), while the lowest (3191) is for NIKKEI 225 of Japan. All stock indices are taken in logarithmic values and then computed in percentage, i.e., $r_t = \ln(\frac{p_t}{p_{t-1}}) \times 100$, where p_t is the stock price index of a country on the t^{th} day.

The same stock indices at monthly frequency for all but HANG SENG of Hong Kong[2] have also been downloaded from the same source. The time series data on the other two variables i.e., money supply (M3 for India, M4 for the UK and M2 for the remaining countries) and discount rate at monthly frequency have been downloaded from the websites of Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/), Bombay Stock Exchange (http://www.bseindia.com/) and Re-

[2]Since the data on money supply for Hong Kong is not available in any public domain, this country has been dropped from the study made with monthly-level data in Chapter 6

serve Bank of India (http://www.rbi.org.in/home.aspx). The span of all these data sets is same as in case of daily data i.e., January 2000 - December 2012.

Data at daily frequency

We first give the plots of the time series of all the eight stock indices in Figure 2.1. It is clear from these plots that all the series are nonstationary having trend - with some stock markets having more than one trend pattern.

Figure 2.1: Time series plots of daily stock indices

All these time series have been found to be nonstationary by the augmented Dickey-Fuller (ADF) test. All these stock indices were then changed to returns and all the return series, as reported in the following section i.e., Section 2.4, have been found to be stationary. The plots of the return series are given in Figure 2.2. Thereafter the summary statistics on returns at daily frequency are presented (*cf.* Table 2.1).

Table 2.1: Summary statistics on daily returns

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
Mean	-0.0006	-0.0004	0.0082	-0.0189	0.0399	0.0661	0.0396	0.0152
Median	0.0488	0.0402	0.0286	0.0051	0.0937	0.1526	0.1117	0.0000
Maximum	10.9572	8.8107	13.4068	13.2345	13.6766	25.2261	15.9899	9.4007
Minimum	-9.4695	-8.7099	-13.5820	-12.1110	-12.0961	20.6571	-11.8092	-9.2561
Std. dev.	1.3508	1.2385	1.6158	1.5667	1.9048	2.3290	1.6517	1.5882
Skewness	-0.1584	-0.1767	-0.0657	-0.3933	-0.0953	-0.1960	-0.1777	-0.0831
Kurtosis	10.3268	8.7030	10.5496	9.6856	6.6994	15.4304	9.3485	7.5141
J-B	7323.49	4479.70	7703.89	6023.19	1837.04	2086.92	5466.37	2829.46
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Obs.	3269	3294	3244	3191	3214	3242	3246	3329

Note: Figures in parentheses indicate $p-$ values. J-B stands for the Jarque-Bera normality test.

The summary statistics on returns of the eight time series are presented in Table 2.1. Mean values of returns for all the BRIC countries are positive. But the same for all the developed economies except Hong Kong are negative. The skewness coefficients for all the return series have negative values, although small in magnitude, indicating that all the returns distributions are skewed to the left with Japan having the maximum asymmetry in distribution. All the kurtosis values are higher than 3 with the maximum being 15.4304 for MICEX of Russia. Consequently, the J-B test statistic values strongly reject the assumption of normality for all the series.

Data at monthly frequency

The plots of the (nominal) returns at monthly frequency as well as those of money supply and discount rate for all the seven time series are given in Figures 2.3, 2.4 and 2.5. It is visually evident that all the series have trend, and the ADF test has concluded that all the series are nonstationary. The indices were converted to returns and all the returns series are found to be stationary. The money supply was changed to growth rate of money supply (GMS) and discount rate to absolute change in discount rate (CDR), and these two transformed series were found to be stationary by the ADF test. The plots of the nominal and real[3] returns along with those of GMS and CDR are given in Figures 2.6, 2.7, 2.8 and 2.9 below.

[3]Real returns have been obtained by adjusting for the CPI inflation.

Table 2.2: Summary statistics on monthly returns of seven countries

	The US	The UK	Japan	Brazil	Russia	India	China
Mean	0.0145	0.0250	-0.4072	0.8474	1.3590	0.8497	0.2522
Median	0.7103	0.8592	0.2444	1.2064	2.3618	1.0305	0.6760
Maximum	10.2307	9.0936	12.0888	16.4813	25.6988	24.8851	24.2526
Minimum	-18.5637	-14.4118	-27.2162	-28.4961	-33.7184	-27.2992	-28.2779
Std. Dev.	4.6613	4.3056	5.9796	7.5594	9.9969	7.5236	8.1473
Skewness	-0.6743	-0.7901	-0.7360	-0.5176	-0.6633	-0.4772	-0.5099
Kurtosis	4.1140	3.8974	4.5191	3.6899	4.2558	4.0732	4.4192
Jarque-Bera	19.7613	21.3254	28.8973	9.9940	21.5520	13.3216	19.7236
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)

Note: $p-$values are given in parenthesis.

Figure 2.2: Time series plots of daily stock returns

The conclusions on the summary statistics on returns are that the mean returns (nominal) are all but Japan positive while for mean return (real), all the three developed markets have negative value and all the emerging economies have positive values. The mean value of GMS is positive for each of the seven countries. As regards CDR , except for China and India, the remaining 5 countries have

Figure 2.3: Time series plots of monthly stock indices of seven countries

Figure 2.4: Time series plots of money supply of seven countries

Figure 2.5: Time series plots of discount rate of seven countries

negative values. Insofar as the distributions are concerned, all the returns as also GMS and CDR have been found to be leptokurtic, in some cases highly. In terms of skewness, all returns have been found to have negative values. Further, the value of the coefficient of skewness is negative for the US, the UK, Japan (for GMS), and the UK , Russia and China (for CDR). Consequently, the assumption of normal distribution is rejected by the J-B test for all variables and for all countries.

Table 2.3: Summary statistics on monthly returns (real) of seven countries

	The US	The UK	Japan	Brazil	Russia	India	China
Mean	-0.1855	-0.1721	-0.3848	0.3232	0.4468	0.3000	0.0627
Median	0.5345	0.4317	0.2444	0.4864	1.3665	0.5738	0.8479
Maximum	10.1698	8.8207	12.2886	15.1795	24.8028	24.2207	22.8623
Minimum	-17.9122	-14.9573	-27.1192	-28.9452	-35.3057	-28.6598	-27.9775
Std. Dev.	4.6433	4.2871	5.9696	7.5548	9.9569	7.6400	8.0934
Skewness	-0.5976	-0.7873	-0.7352	-0.5182	-0.6886	-0.4939	-0.5274
Kurtosis	3.9078	3.8903	4.5103	3.6659	4.3573	4.0504	4.3459
Jarque-Bera	14.5482	21.1305	28.6951	9.7992	24.1487	13.4280	18.8850
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)

Note: $p-$values are given in parenthesis.

Table 2.4: Summary statistics on growth rate of money supply of seven countries

	The US	The UK	Japan	Brazil	Russia	India	China
Mean	0.5214	0.4616	0.1794	1.2115	2.3573	1.2856	1.3445
Median	0.5264	0.5961	0.0704	1.0867	2.2624	1.0774	1.2495
Maximum	2.6977	3.1759	2.1041	6.3082	12.1975	5.7334	6.1337
Minimum	-1.5668	-25.0961	-1.0347	-3.2886	-12.6774	-0.5069	-1.0166
Std. Dev.	0.6609	2.2383	0.5112	1.7355	3.4588	1.0250	1.1008
Skewness	-0.10584	-9.66806	0.837207	0.245495	-0.10703	1.26336	0.771748
Kurtosis	3.92956	111.1875	4.233477	3.853782	5.851783	5.557166	4.962763
Jarque-Bera	5.869936	78006.46	27.93314	6.264676	52.81942	83.46371	40.26651
	(0.05)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.00)

Figure 2.6: Time series plots of monthly returns (nominal) of seven countries

Note: $p-$values are given in parenthesis.

Table 2.5: Summary statistics on change in discount rate

	The US	The UK	Japan	Brazil	Russia	India	China
Mean	-0.0274	-0.0339	-0.0013	-0.0499	-0.2371	0.0065	0.0001
Median	0.0000	0.0000	0.0000	-0.0263	0.0000	0.0000	0.0000
Maximum	1.5000	0.2500	0.3500	5.9797	1.0000	3.5000	0.8100
Minimum	-0.9800	-1.5000	-0.2500	-2.6257	-12.0000	-1.0000	-1.0800
Std. Dev.	0.2357	0.1934	0.0490	0.7759	1.1463	0.3159	0.1347
Skewness	0.6191	-3.9849	2.2112	2.9773	-7.7629	8.6885	-1.4878
Kurtosis	15.3479	27.2191	33.9315	26.4916	75.0340	99.2449	41.3293
Jarque-Bera	994.6013	4198.4447	6305.3820	3793.0506	35068.4024	61774.1579	9545.3683
Probability	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

Note: $p-$values are given in parenthesis.

Figure 2.7: Time series plots of monthly returns (real) of seven countries

Figure 2.8: Time series plots of growth rate of money supply of seven countries

Figure 2.9: Time series plots of change in discount rate of seven countries

2.4 Characteristics of Data

Data at daily frequency

To find the important characteristics of all the data sets, we have carried out some tests, the results of which presented in Table 2.6. The properties of the time series we are basically interested in are: stationarity, autocorrelation (both linear and squared dependences) and structural breaks.

All the return series have been found to be stationary by the ADF test[4]. This is evident from the ADF test statistics values given for return series in Table 2.6. In the ADF estimating equations for all the eight return series, the linear deterministic trend term has been found to be statistically insignificant. Also, all the return series were found to have (linear) autocorrelations as well as squared autocorrelation, as exhibited by the values of $Q(5)$, $Q(10)$ and $Q^2(5)$ and $Q^2(10)$ test statistics, indicating presence of these dependences in all the series.

Existence of structural breaks were carried out by the Bai-Perron (1998, 2003) test. In their paper, Bai and Perron (1998) first considered estimating multiple structural changes, occurring at unknown time points, in a linear model, by the method of least squares. The results were obtained under a general framework which also allows a subset of the parameters not to change. In that paper, they considered the problem of testing for multiple structural changes under very general conditions of the data and the errors.

Table 2.6: Unit root and autocorrelation tests of daily stock returns

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
ADF	-44.8862	-29.4025	-57.9345	-58.0037	-55.8956	-54.5714	-53.1177	-57.4490
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q(5)$	42.0542	48.4091	7.5071	7.0895	13.8192	12.1271	21.5550	10.2975
	(0.00)	(0.00)	(0.19)	(0.21)	(0.02)	(0.03)	(0.00)	(0.07)
$Q(10)$	49.1160	64.2120	17.7793	14.1138	23.1694	15.7780	38.5307	18.9498
	(0.00)	(0.00)	(0.06)	(0.17)	(0.01)	(0.11)	(0.00)	(0.04)
$Q^2(5)$	1340.2018	1302.9052	1351.6053	1617.4151	943.6102	560.6082	522.6123	250.7641

Continued on next page

[4]The estimating equation with an intercept and a linear trend term has been used. The lag value in this equation has been decided by the SIC criteria

Table: 2.6 *Continued from previous page*

	the US	the UK	Hong Kong	Japan	Brazil	Russia	India	China
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q^2(10)$	2609.1054	2122.8019	2026.8029	2589.5043	1903.1032	835.0211	845.1342	454.6938
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
D_{max}	14.66	14.67	8.56	5.31	6.82	7.62	14.37	11.46
WD_{max}	14.66	18.57	10.17	9.44	9.89	12.34	18.18	14.49

Note: $p-$values are given in parenthesis.

Their model allows for general forms of serial correlation and heteroskedasticity of the errors, lagged dependent variables, trended regressors as well as different distributions for the errors and the regressors across segments. It may be noted that since their framework also allows for partial structural change, this leads to potential savings in the number of degrees of freedom, and this is particularly relevant for multiple changes. They proposed a few test statistics for identifying multiple break points. In Table 2.6, we report the results[5] of the D_{max} and WD_{max} test statistics of Bai and Perron with the value of the trimming parameter being set to 0.15.

It is evident from the D_{max} test statistic values presented in Table 2.6 that at 1% level of significance the computed values are less than the critical value of 5.4 for each of the eight returns series, leading to the conclusion that the null hypothesis of 'no structural break' cannot be rejected, and hence all the series are found to be structurally stable. The conclusion by the WD_{max} test remains the same for all but SENSEX (India) and FTSE ALL (the UK) indices. For these two series, the test statistic values were found to have just exceeded the critical value of 17.01 at 1% level of significance. Combing these findings, it can be concluded that all the eight return series are structurally stable. It may be pointed out that this does not necessarily mean that the original time series of stock price indices are free from structural breaks. Since returns are stationary, there is obviously no trend. But there may very well be break in trend due to global financial crisis in 2008. However, since we are concerned primarily with the risk-return relationship, we have confined ourselves to testing for breaks in the stationary return series only.

Further, absence of structural breaks does not necessarily mean that there is no regime shift in the return series. Regimes can be defined in several ways, based on the definition of transition variable.

[5]Codes available from the website of P. Perron, http://people.bu.edu/perron/, have been used for carrying out tests for multiple structural breaks

When the transition variable is taken as 'time', the regime shift is the same as structural break. In our case, we have used the average value of past returns as the transition variable, and accordingly defined the two regimes. Naturally, a structurally stable return series can very well have different regimes characterised by market movements like up and down.

Data at monthly frequency

Tables 2.7 through 2.10 present the results of all the tests done with the monthly data for all the series. All the monthly return series (both nominal and real) have been found to be stationary by the ADF test, as reported in Table 2.6. We have checked for seasonality in all the series, but seasonality was not found to be statistically significant in all but Consumer price index (CPI) of the USA . Accordingly, this series i.e., CPI (the USA) was seasonally adjusted for.

Table 2.7: Unit root and autocorrelation tests of monthly returns

	the US	the UK	Japan	Brazil	Russia	India	China
ADF	-10.7028	-11.3616	-10.662	-10.8036	-10.4495	-11.2819	-6.73684
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q(1)$	3.2309	1.0905	2.9311	2.6178	4.4636	1.2351	0.7605
	(0.07)	(0.30)	(0.09)	(0.11)	(0.04)	(0.27)	(0.38)
$Q(5)$	7.9963	7.5808	5.1856	3.0222	6.5456	4.1976	19.677
	(0.16)	(0.18)	(0.39)	(0.70)	(0.26)	(0.52)	(0.00)
$Q(10)$	12.171	10.505	7.9136	9.106	13.329	6.1148	22.977
	(0.27)	(0.40)	(0.64)	(0.52)	(0.21)	(0.81)	(0.01)
$Q^2(1)$	11.38405	8.696474	3.838585	2.144818	14.27918	0.45669	0.218346
	(0.00)	(0.00)	(0.05)	(0.14)	(0.00)	(0.50)	(0.64)
$Q^2(5)$	33.1044	21.89252	5.436235	2.888957	29.81355	3.551425	27.04608
	(0.00)	(0.00)	(0.36)	(0.72)	(0.00)	(0.62)	(0.00)
$Q^2(10)$	35.76303	35.27608	10.32308	7.98602	48.58084	21.84949	66.93242
	(0.00)	(0.00)	(0.41)	(0.63)	(0.00)	(0.02)	(0.00)

Note: $p-$values are given in parenthesis.

The values of the Ljung-Box $Q(\cdot)$ test suggest that most of the return series are non-autocorrelated except SSE Composite of China, where we found that 1^{st} order autocorrelation is absent but there are higher order autocorrelations which have significant values. In case of the US, Japan and Russia, $Q(1)$ is rejected at 7%, 9% and 4% levels of significance. Squared autocorrelations are present in the stock returns of the US, the UK, Russia and China. Stock returns of India have been found to have squared autocorrelations in higher orders only.

Table 2.8: Unit root and autocorrelation tests of monthly real returns

	The US	The UK	Japan	Brazil	Russia	India	China
ADF	-10.9134	-11.3150	-10.6891	-10.8541	-10.3604	-11.2092	-6.8183
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q(1)$	2.4531	1.1510	2.8426	2.4691	4.7549	1.3775	0.9309
	(0.12)	(0.28)	(0.09)	(0.12)	(0.03)	(0.24)	(0.33)
$Q(5)$	7.7568	7.9626	4.8344	3.0825	6.9924	3.8785	19.3439
	(0.17)	(0.16)	(0.44)	(0.69)	(0.22)	(0.57)	(0.00)
$Q(10)$	12.3464	11.0599	7.3828	9.2211	13.0838	5.5430	22.6124
	(0.26)	(0.35)	(0.69)	(0.51)	(0.22)	(0.85)	(0.01)
$Q^2(1)$	9.6029	9.0979	3.9175	2.0131	16.2920	0.1744	0.1643
	(0.00)	(0.00)	(0.05)	(0.16)	(0.00)	(0.68)	(0.69)
$Q^2(5)$	34.6689	20.9013	5.1304	2.9432	30.9214	4.6693	28.3021
	(0.00)	(0.00)	(0.40)	(0.71)	(0.00)	(0.46)	(0.00)
$Q^2(10)$	37.7815	31.2551	10.2566	7.5746	49.9048	22.2355	69.1073
	(0.00)	(0.00)	(0.42)	(0.67)	(0.00)	(0.01)	(0.00)

Note: $p-$values are given in parenthesis.

In case of real returns, the characteristics are more or less same as in nominal stock returns, as is evident from Table 2.7. In Table 2.9, we report the results of the aforesaid tests for growth rate of money supply (GMS) for all the 7 countries. Here, we find that the ADF test cannot reject the null hypothesis of unit root in case of the USA, Japan, Brazil and India. But the PP test suggests rejection of null of unit root for these four as well as for the remaining three series. Since for these four series, contradictory conclusions are obtained by the ADF and the PP tests, we carried out the confirmatory KPSS test. The results of this test are also reported in Table 2.9. It is found that this test can not reject its null hypothesis of stationarity for all the eight series. Hence, we conclude that GMS series of all the countries including the USA, Japan, Brazil and India are stationary.

Table 2.9: Unit root and autocorrelation tests of growth rate of money supply

	The US	The UK	Japan	Brazil	Russia	India	China
ADF	-2.71458	-11.9447	-1.88247	-2.79392	-3.41707	-1.72743	-5.44108
	(0.23)	(0.00)	(0.66)	(0.20)	(0.05)	(0.73)	(0.00)
PP	-11.7807	-11.9752	-13.8888	-12.4084	-14.3721	-12.403	-14.303
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
KPSS	0.084548	0.076994	0.057958	0.083305	0.058298	0.157896	0.065608
$Q(1)$	0.1399	0.2938	0.2511	0.0465	2.3674	0.0001	3.5569
	(0.71)	(0.59)	(0.62)	(0.83)	(0.12)	(0.99)	(0.06)
$Q(5)$	14.3350	3.2277	43.9975	6.9177	9.3795	5.8366	31.0684
	(0.01)	(0.66)	(0.00)	(0.23)	(0.09)	(0.32)	(0.00)
$Q(10)$	36.5379	4.8610	98.2930	16.1291	29.2325	24.5888	60.1326
	(0.00)	(0.90)	(0.00)	(0.10)	(0.00)	(0.01)	(0.00)
$Q^2(1)$	2.7749	0.0159	1.9578	8.3542	0.2015	0.0204	0.2633
	(0.10)	(0.90)	(0.16)	(0.00)	(0.65)	(0.89)	(0.61)
$Q^2(5)$	7.4716	0.0591	9.0275	9.3217	6.7665	3.2343	9.1992
	(0.19)	(1.00)	(0.11)	(0.10)	(0.24)	(0.66)	(0.10)
$Q^2(10)$	12.0337	0.0809	26.8009	17.7335	13.8024	14.6815	21.7077
	(0.28)	(1.00)	(0.00)	(0.06)	(0.18)	(0.14)	(0.02)

Note: $p-$values are given in parenthesis. The critical values of KPSS test are 0.216, 0.146 and 0.119 at 1%, 5% and 10% level respectively

Here we also see that autocorrelation is present only in the higher lags, but lower order autocorrelations are absent. Autocorrelations in the squared values are also absent except for Brazil. Japan and China are found to have significant squared autocorrelations for lag 10 , but in lower orders these are insignificant. All the remaining series have no autocorrelations in level as well as in squared values.

Table 2.10: Unit root and autocorrelation tests of change in discount rate

	The US	The UK	Japan	Brazil	Russia	India	China
ADF	-6.8739	-6.2347	-11.8300	-5.1269	-13.4667	-12.3575	-11.0699

Continued on next page

Table: 2.10 Continued from previous page

	The US	The UK	Japan	Brazil	Russia	India	China
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Q(1)$	44.0372	56.2880	0.2511	32.0140	0.1313	0.0397	1.7194
	(0.00)	(0.00)	(0.62)	(0.00)	(0.72)	(0.84)	(0.19)
$Q(5)$	107.0042	104.8666	3.1297	84.3972	17.4430	2.8132	1.7194
	(0.00)	(0.00)	(0.68)	(0.00)	(0.00)	(0.73)	(0.89)
$Q(10)$	149.1243	107.5040	22.8586	112.2783	22.7136	3.0781	18.1541
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.98)	(0.05)
$Q^2(1)$	0.9896	36.3659	0.0837	0.2290	0.0288	0.0151	0.0449
	(0.32)	(0.00)	(0.77)	(0.63)	(0.87)	(0.90)	(0.83)
$Q^2(5)$	2.3747	42.7232	1.0537	4.3613	4.5259	0.0634	0.4582
	(0.80)	(0.00)	(0.96)	(0.50)	(0.48)	(1.00)	(0.99)
$Q^2(10)$	2.6343	43.0662	23.9163	5.8307	5.0889	0.1182	21.4625
	(0.99)	(0.00)	(0.01)	(0.83)	(0.89)	(1.00)	(0.02)

Note: $p-$values are given in parenthesis.

The time series of change in discount rate (CDR) is stationary as the ADF test rejects the null hypothesis of unit root with $p-$value 0.00 for all the countries (see, Table 2.10). Lower-order autocorrelations are present in the time series of the US, the UK and Brazil. For the remaining series, lower-order autocorrelations are absent. But in case of $Q(10)$, we have found significant autocorrelations in all countries except for India. Autocorrelations in squared values are found to be absent in all the series except for the UK. Finally, since all the series were found to have no structural breaks at daily frequency, this test was not done for the data sets at monthly frequency.

2.5 Conclusions

In this chapter, apart from plots of all the data sets, summary statistics and results of tests for stationarity, presence of autocorrelations (both linear and squared), and the Bai-Perron test of structural breaks have been presented. All the return series have been found to be stationary having no structural breaks. As for the two instruments for monetary policy *viz.*, money supply and discount rate, these two have been found to be nonstationary. However, growth rate of money supply and change in discount rate are stationary.

Chapter 3

Risk-Return Relationship in EGARCH-in-Mean Framework Under Up and Down Market Movements

3.1 Introduction

Modelling stock market volatility has been the subject of vast theoretical and empirical investigations during the last three decades by academics and practitioners alike. Initially, volatility, as measured by the standard deviation or variance of returns, which is obviously constant, was used as a crude measure of the total risk of financial assets. However, this assumption of constant risk was found to be very restrictive, particularly in the context of financial time series, and researchers started looking for models capturing time-varying volatility. This led to the seminal work by Engle (1982) where he proposed a model for asset volatility, now well-known as the autoregressive conditional heteroscedastic (ARCH) model. Subsequently, its generalization was suggested by Bollerslev (1986), which is called the generalized ARCH (GARCH) model. One of the primary restrictions of ARCH/GARCH class of models is that it imposes the symmetric response of volatility to positive and negative shocks. However, it has been argued that due to 'leverage effect', volatility of stock returns is often asymmetric in nature. There are two popular models capturing asymmetric volatility, and one of these is due to Nelson (1991), called the exponential GARCH (EGARCH) model, and the other due to Glosten *et al.* (1993), known as the GJR GARCH model (sometimes also called the threshold GARCH (TGARCH) model).

While there are many models capturing asymmetry in conditional variance, conditional mean models from similar consideration are rather limited. In the context of finance literature, in general, it has long been investigated whether or not the asymmetric risk or beta of the capital asset pricing model(CAPM), due to Markowitz (1959), responds asymmetrically to good and bad news as measured by positive and negative returns, respectively. More generally, many studies (see, for instance Kim and Zumwalt (1979), Bharadwaj and Brooks (1993), Pettengil, Sundaram and Mathur (1995), Howton and Peterson (1998), Crombez and Vandetr Vennet (2000), and Faff (2001)) have examined the validity of the asset pricing models, especially the CAPM, taking into account the market movements, defined as the 'up' and 'down' markets. To classify 'up' and 'down' markets, various definitions have been used. For instance, Kim and Zumwalt (1979) and Chen (1982) have used three threshold levels *viz.*, average monthly market return, average risk free rate and zero. When the realized market return is above (below) the threshold level, the market is said to be in the up (down) market state. When the threshold value is taken to be zero for market returns at monthly or quarterly frequency, the up and down markets are often called the bull and bear markets. The overwhelming empirical evidence in empirical studies with different states of market condition is that the CAPM assuming constant risk cannot participate in different market conditions. Levy (1974), and Fabozzi and Francis (1977) suggested that there is a need to separate betas between bull and bear markets. By defining the bull and bear markets using a threshold model, Kim and Zumwalt (1979) found no evidence to support the beta instability, but concluded that investors should like to receive a positive premium for accepting downside risk, while a negative premium was associated with the up-market beta. Using daily return data, Granger and Silvapulle (2002) investigated the asymmetric response of beta to different market conditions by modelling the mean and the volatility of CAPM as nonlinear threshold models with three regimes. Galagedera and Faff (2005) have also investigated whether the risk-return relation varies, depending on changing market volatility and up-down market conditions.

To capture such 'asymmetries' or different effects understood by different market conditions, the threshold autoregressive (TAR) models, originally due to Tong (1978), have been used. Such models are linear locally but nonlinear overall. This class of models is characterized by a regime switching mechanism. Several models where such consideration to conditional mean along with volatility, especially of symmetric GARCH kind, have been proposed. For instance, Li and Li (1996) introduced the double threshold GARCH (DTGARCH) model. However, models for returns with asymmetry characterized by market conditions like the bull and bear markets, which are considered to be broad market movements that can be illustrated using low frequency data(see, for relevant details, Chen (1982), Gonzalez *et* *al.*(2006), and Chen (2009)), along with asymmetry in conditional variance characterized by leverage effect, is very limited. In case of the latter, mention may be made of Hagerud (1997) who proposed the smooth transition ARCH model. Gonzalez-Rivera (1998) used the smooth transition GARCH (STGARCH) model. Lundberg and Terasvirta (1998) used a STAR model for conditional mean and the smooth transition GARCH (STGARCH) which is a modification of the TGARCH model of Glosten *et al.* (1993) for the conditional variance. Brannas and DeGoojer (2004) combined an asymmetric moving average model for the asymmetric mean equation with an asymmetric quadratic GARCH model for the conditional variance equation.

In the literature on 'risk-return' relationship, all the models proposed till the publication of the paper by Engel *et al.* in 1987 were of the kind where risk was assumed to have no direct effect on returns. They proposed the ARCH-in-mean (ARCH-M) model which incorporated risk premium by introducing volatility directly into the conditional mean equation of returns so that risk, *inter alia*, could affect returns directly. Although such a risk-return relationship is expected to be positive since an increase in risk represented through conditional variance is likely to lead to a rise in expected return, the empirical evidence is somewhat mixed. In respect of correlation behaviour of stock returns and subsequent volatility, French, Schwert and Stambaugh (1987) and Campbell and Hentschel (1992) have found the relative risk aversion parameter, the parameter linking volatility to return in the mean equation, to be positive, while Turner *et al.* (1989) have found it to be negative. As noted by Bekaert and Wu (2000), sometimes this coefficient has been found to be statistically insignificant as well. If the relation between market conditional volatility and the market return is not found to be positive, then the validity of time-varying risk premium is in doubt. However, it might as well be due to the fact that in this theory the relative risk aversion parameter is taken to be constant, which indeed may not be true in some situations, leading to possible error in the estimate of the parameter concerned and consequently of inferences thereof.

Therefore, consideration to different market movements[1] in conditional mean as also to asymmetry in conditional variance in terms of behaviour of return shocks in the GARCH-in-mean (GARCH-M) modelling framework, should yield a better understanding of the 'risk-return' relationship. It is important to note that in this framework it is possible to find if the associated risk responds differently to different states of stock markets. In fact, this enables us to test the conclusion of Kim and Zumwalt (1979) that investors would like to receive a positive (negative) premium for accepting down (up) market

[1]There are some studies where asymmetry in mean in terms of return shocks , which is also called the asymmetric reverting behaviour in return dynamics, have been considered while specifying the model for conditional mean (see, for details, Nam *et al.* (2001), and Nam (2003), Kulp-Tåg (2007)).

risk. To the best of our knowledge, there is no such study which considers two different relative risk aversion parameters in this framework with daily-level stock returns.

This paper proposes two such models each with different risk aversion parameters for two different regimes based on average past returns - to be henceforth called as - up and down markets. The conditional variance model is taken to be the EGARCH model. We have also considered a similar model with (symmetric) GARCH specification for conditional variance. One of the proposed models considers smooth transition mechanism in the conditional mean process, which was proposed by Chan and Tong (1986) and Terasvirta (1994). The proposed models along with two other existing models *viz.*, the AR-GARCH-M and AR-EGARCH-M, which are taken as benchmark models, have been fitted to individual time series of stock returns of eight countries comprising four advanced economies - the USA, the UK, Hong Kong, and Japan - and four important emerging economies - called the BRIC group - Brazil, Russia, India, and China. The reasons for choosing these countries has been stated in Section 2.2 of Chapter 2. The benchmark models have been considered in order to find to what extent the performances of the proposed models improve with the introduction of (*i*) up and down movements of the stock market, and (*ii*) two different risk aversion parameters for these two states.

The organization of the paper is as follows. In Section 3.2, the proposed models are introduced. The estimation results are discussed in Section 3.3. Inferences based on statistical tests are presented in the next section. The paper ends with some concluding remarks in Section 3.5.

3.2 The Proposed Models

As discussed in the preceding section, all the three proposed models for returns at daily frequency, r_t, have the following conditional mean specification[2]:

$$r_t = \begin{cases} \mu_1 + \phi_1 r_{t-1} + \delta_1 \sqrt{h_t} + \varepsilon_t, & \text{if } \bar{r_t}^k \leq 0 \\ \mu_2 + \phi_2 r_{t-1} + \delta_2 \sqrt{h_t} + \varepsilon_t, & \text{if } \bar{r_t}^k > 0 \end{cases} \tag{3.1}$$

where $\varepsilon_t = \nu_t \sqrt{h_t}$ with $\varepsilon_t | \psi_{t-1} \sim N(0, h_t)$, ν_t is independently and identically distributed $N(0,1)$, ψ_{t-1} is the information or conditioning set up to time $t-1$, h_t is the conditional variance at time t and $\bar{r_t}^k$ is as defined below.

[2]The model has been specified with one lag only since this was found to be adequate in empirical analysis for all the return series. Further, $\sqrt{h_t}$ has been considered in specifying the risk premium term, although other functional forms like h_t and $\ln h_t$ can as well be taken.

In the literature on threshold autoregressive (TAR) model, the choice of threshold variable is often taken to be a past value of its own. In our case, the threshold variable, as stated in Section 3.1, is taken to be $\bar{r_t}^k$, where $\bar{r_t}^k$ is the average of the past k daily returns i.e., $\bar{r_t}^k = \frac{\sum_{i=1}^{k} r_{t-i}}{k}$. Obviously, appropriate choice of k is a relevant issue. What we have done is to make several choices of k and then choose the one for which the underlying likelihood value for our model is maximum.

Combining the two conditional mean specifications stated in equation(3.1), we can write the model as

$$r_t = (\mu_1 + \phi_1 r_{t-1} + \delta_1 \sqrt{h_t}) I(\bar{r_t}^k \leq 0) + (\mu_2 + \phi_2 r_{t-1} + \delta_2 \sqrt{h_t})(1 - I(\bar{r_t}^k \leq 0)) + \varepsilon_t \tag{3.2}$$

where $I(\cdot)$ is an indicator function taking value 1 if $\bar{r_t}^k \leq 0$ and 0 otherwise.

Little is known about the rigorous derivations of the conditions for stationarity of nonlinear time series models. In general Chan and Tong (1985) have shown that a sufficient condition for stationarity of TAR model is $\max(|\phi_1|, |\phi_2|) < 1$. Chan *et al.* (1985) has derived less restrictive sufficient conditions. The conditions on the intercepts μ_1 and μ_2 are such that the time series has a tendency to revert to the stationary regime, and the time series is globally stationary. As noted by Franses and van Dijk (2000), a 'rough and ready' check for nonstationarity of nonlinear time series model, in general, is to find if the skeleton is stable. This intuitively means that if the time series tends to explode for certain initial values of the parameters, then the series is nonstationary, and this can be checked by simulation.

The first proposed model, called the TAR-GARCH-M, assumes h_t to have the GARCH(1,1) specification[3] i.e.,

$$h_t = \omega + \alpha \varepsilon_{t-1}^2 + \beta h_{t-1} \tag{3.3}$$

where $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$, and $\alpha + \beta \leq 1$. In case of the second model, designated as the TAR-EGARCH-M, h_t is taken to be the EGARCH(1,1) model[3] which is given by

$$\ln h_t = \omega + \alpha_1 \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \lambda \left[\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} - E\left(\frac{|\varepsilon_{t-1}|}{\sqrt{h_{t-1}}} \right) \right] + \beta_1 \ln h_{t-1} \tag{3.4}$$

Unlike (symmetric) GARCH model, no restrictions on parameters of EGARCH model are needed to be imposed to ensure that h_t is positive. Note that for EGARCH$(1,1)$, if $0 < \lambda < 0$, then the process generates volatility clustering while this condition along with $\alpha_1 < 0$ delivers a leverage effect since under the restrictions, negative shock has a leverage effect on the conditional variance than positive shock of the same size.

[3]The orders $(1,1)$ for the GARCH/EGARCH model was found to be adequate for all the return series, and hence the model has been specified for these orders only.

This model assumes that the border between the two regimes signifying change in mean is given by a specific value of the threshold variable, which is 0 for our model. A more gradual transition between different regimes can be obtained by replacing the indicator function $I(\bar{r_t}^k \leq 0)$ in equation (3.2) by a continuous function $G(\bar{r_t}^k, \gamma)$ which changes smoothly from 0 to 1 as $\bar{r_t}^k$ increases. The resulting model based on this transition mechanism was first introduced by Terasvirta (1994) in the context of capturing regime switching behaviour of financial variables, and it is called the smooth transition autoregressive (STAR) model. While this model has been extensively used in capturing regime switching behaviour, it is recently being also applied to incorporate asymmetry in conditional variance through regime-shifting consideration (see, for instance, Nam *et al.* (2001), and Nam (2003)).

We propose our last model by considering the STAR model for the conditional mean i.e., by replacing the indicator function in equation (3.2) with a popular smooth transition function *viz.*, the logistic function, for the conditional mean and assuming, as before, the EGARCH(1,1) specification, for the conditional variance. This model, called the smooth transition autoregressive model with EGARCH-in-mean (STAR-EGARCH-M), is represented as

$$r_t = (\mu_1 + \phi_1 r_{t-1} + \delta_1 \sqrt{h_t})(1 - G(\bar{r_t}^k; \gamma)) + (\mu_2 + \phi_2 r_{t-1} + \delta_2 \sqrt{h_t}) G(\bar{r_t}^k; \gamma) + \varepsilon_t \tag{3.5}$$

and the specification of h_t is as given in equation (3.4) where $G(\bar{r_t}^k; \gamma) = \frac{1}{(1+exp^{-\gamma \bar{r_t}^k})}$. This transition function takes a value between 0, and 1 depending on the value of $\bar{r_t}^k$ i.e., $0 < G(\bar{r_t}^k; \gamma) < 0.5$ for $\bar{r_t}^k < 0$, $G(\bar{r_t}^k; \gamma) = 0.5$ for $\bar{r_t}^k = 0$ and $0.5 < G(\bar{r_t}^k; \gamma) < 1$ for $\bar{r_t}^k > 0$. The parameter, γ, determines the smoothness of the change in the value of the logistic function, and thus the transition from one regime to the other. When the parameter γ approaches 0, yielding $G(\bar{r_t}^k; \gamma) \simeq 0.5$, the STAR-EGARCH-M model reduces to a simple AR-EGARCH-M model. When, on the other hand, γ approaches infinity, the transition function becomes $G(\bar{r_t}^k; \gamma) = 1$ for $\bar{r_t}^k > 0$ and $G(\bar{r_t}^k; \gamma) = 0$ for $\bar{r_t}^k \leq 0$ so that it reduces to an indicator function.

3.3 Estimation Results

In this section we discuss the results of estimation of all the models considered in this chapter. As stated in Chapter 2 the stock index data at daily frequency from 01 January 2000 to 31 December 2012 for eight countries - four from advanced countries and four from important emerging economics - have been considered for this study. Specifically, the countries in these two groups are the USA, the UK, Hong Kong and Japan for the advanced economics, and Brazil, Russia, India and China for the important emerging economies. The stock indices, as already stated, considered for this study are S&P 500 (for the US), FTSE ALL (for the UK), HANG SENG (for Hong Kong) , NIKKEI 225 (for Japan), BOVESPA (for Brazil), MICEX (for Russia), SENSEX (for India), and SSE COMPOSITE (for China).

3.3.1 Findings on the existing models

In this study, we have considered, in all, five models and obtained the ML estimates of the parameters involved. Besides the three proposed models - TAR-GARCH-M, TAR-EGARCH-M and STAR-EGARCH-M - the two others are AR-GARCH-M and AR-EGARCH-M. The two latter models refer to two simple models in 'volatility-in-mean' framework, which may as well be considered as benchmark models, where the conditional mean model has no consideration to stock market movements and the conditional volatility model is taken to be GARCH and EGARCH for the two models, respectively. These two models, therefore, are special cases of the models proposed in this paper. These models are considered to find to what extent consideration to up and down market movements in conditional mean with and/or asymmetry in conditional variance captured through EGARCH model leads to improvement in explaining return dynamics, and the consequent impact of the same on risk aversion parameter and hence on risk premium.

Assuming the distributional assumption about ε_t to be normal i.e., $\varepsilon_t|\psi_{t-1} \sim N(0, h_t)$, the likelihood function is written which is obviously highly nonlinear. Imposing stationarity conditions, the programmes for obtaining the ML estimates of the parameters of these models, have been written in GAUSS. The computations involved were substantial. In all cases, global convergence of the underlying nonlinear objective function has been achieved. The parametric restrictions imposed from consideration of stationarity and finite unconditional variance of GARCH i.e., $-1 < \phi_1, \phi_2 < 1$, $\omega > 0$, $\alpha \geq 0$, $\beta \geq 0$ and $\alpha + \beta < 1$ were taken into the algorithms. The ML estimates thus obtained for all the models are reported and discussed below.

We first report the estimates of the AR-GARCH-M[4] model for all the eight return series in Table 3.1. In the context of our study, this is the simplest model since it considers neither different market movements like up and down for conditional mean nor leverage effect in conditional variance.

Table 3.1: Estimates of the parameters of the AR(1)- GARCH(1,1)- M model

[4]Since the AR model for the conditional mean has been found to be adequate with lag 1, and the orders of GARCH/EGARCH model for the conditional variance have been obtained as (1,1) for all the eight return series, these orders are not mentioned in the text.

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
μ	-0.0078	-0.0011	0.0129	0.0536	-0.1506	0.1290	0.0941	-0.1119
	(0.87)	(0.97)	(0.83)	(0.47)	(0.23)	(0.20)	(0.17)	(0.16)
ϕ	-0.0586	-0.0450	0.0149	-0.0044	0.0112	0.0238	0.0797	0.0036
	(0.00)	(0.01)	(0.41)	(0.81)	(0.54)	(0.20)	(0.00)	(0.84)
δ	0.0597	0.0568	0.0346	-0.0106	0.1421	-0.0018	0.0048	0.1030
	(0.22)	(0.21)	(0.50)	(0.86)	(0.06)	(0.97)	(0.93)	(0.09)
ω	0.0151	0.0132	0.0142	0.0417	0.0655	0.0902	0.0551	0.0288
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α	0.0864	0.1141	0.0671	0.1052	0.0720	0.1056	0.1291	0.0625
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9043	0.8799	0.9271	0.8794	0.9086	0.8767	0.8527	0.9267
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLLV	-4862.34	-4679.87	-5529.85	-5527.33	-6312.96	-6706.28	-5684.69	-5895.71

In Table 3.1, we specify the following models for r_t and h_t:

$$r_t = \mu + \phi r_{t-1} + \delta\sqrt{h_t} + \varepsilon_t \qquad , \varepsilon_t|\psi_{t-1} \sim N(0, h_t)$$
$$h_t = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}.$$

The entries in the parentheses are the $p-$ values; MLLV is the maximized log-likelihood value.

It is noted that the intercept μ is statistically insignificant for all the series. The first-order autocorrelation coefficient ϕ is significant only for three returns series *viz.*, SENSEX for India, S&P 500 for the USA and FTSE ALL for the UK. The coefficients of GARCH model are significant at 1% level for all the return series indicating presence of strong volatility in all the series. From consideration of risk-return relationship, the risk aversion parameter, δ, is the most important one. And the findings on δ are somewhat unexpected since for all the return series, δ is statistically insignificant meaning thereby that time-varying risk does not directly influence returns irrespective of whether the stock markets refer to advanced or BRIC group of emerging economies. This has been observed by others as well. For instance, Bekaert and Wu (2000) have stated that it is often found that the coefficient linking volatility to return is statistically insignificant. Of course, if the relation between market conditional volatility and market expected return is not positive, then the validity of the time-varying risk premium set-up is in doubt. Such a finding for returns on all the eight stock markets raises the question of asymmetry in volatility not being duly considered in the analysis, especially because leverage effect is so common and prevalent in stock returns.

Table 3.2: Estimates of the parameters of the AR(1)-EGARCH(1,1)-M model

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
μ	0.0409	0.0077	0.0733	0.0866	-0.0947	0.0152	0.0867	-0.0365
	(0.30)	(0.83)	(0.21)	(0.23)	(0.42)	(0.09)	(0.18)	(0.63)
ϕ	-0.0541	-0.0292	0.0235	-0.0085	0.0263	0.0161	0.0907	0.0047
	(0.00)	(0.10)	(0.19)	(0.68)	(0.15)	(0.38)	(0.00)	(0.79)
δ	-0.0434	-0.0001	-0.0432	0.0770	0.0771	-0.0419	-0.0318	0.0562
	(0.34)	(0.99)	(0.39)	(0.19)	(0.28)	(0.43)	(0.54)	(0.34)
ω	0.0046	-0.0005	0.0107	0.0218	0.0312	0.0438	0.0306	0.0180
	(0.07)	(0.84)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α	-0.1274	-0.1247	0.0628	-0.0980	-0.0819	-0.0457	-0.0997	0.0192
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
λ	0.1067	0.1224	0.1301	0.1867	0.1284	0.2246	0.2431	0.1207
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9832	0.9830	1.9869	0.9697	0.9724	0.9733	0.9631	0.9873
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLLV	-4791.03	-4606.78	-5497.61	-5490.22	-6284.19	-6712.23	-5660.92	-5893.71

In Table 3.2 we specify the following models for r_t and h_t:

$$r_t = \mu + \phi r_{t-1} + \delta\sqrt{h_t} + \varepsilon_t, \qquad \varepsilon_t|\psi_{t-1} \sim N(0, h_t)$$
$$\ln h_t = \omega + \alpha\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \lambda\left[|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}| - \sqrt{\frac{2}{\pi}}\right] + \beta\ln h_{t-1}.$$

The entries in the parentheses are the $p-$ values; MLLV is the maximized log-likelihood value.

The estimation results for the AR-EGARCH-M model where instead of GARCH, conditional variance is taken to be the EGARCH model are presented in Table 3.2. It is noted from this table that the first-order autocorrelation coefficient is significant only for three series i.e., SENSEX, S&P 500 and FTSE ALL, which are, as expectedly, the same as obtained in case of the AR-GARCH-M model. From the estimates of the parameters of the EGARCH model, it is found that all the four parameters i.e., ω, α, λ and β are significant for all the eight series. The parameter α has been found to be negative for all but returns on SSE COMPOSITE of China and HANG SENG of Hong Kong. For these two countries $\hat{\alpha}$ has been found to be 0.0192 and 0.0628, respectively. Thus, while asymmetry in volatility in returns of all the eight developed and emerging economies have been empirically found, it may be worthwhile to note that the nature of this asymmetry is somewhat mixed, as also noted by Bekaert and Wu (2000). To be more specific, in six out of eight markets, the relationship between current volatility and past returns is found to be negative, which is indeed often the case (see, for instance, Turner *et al.* (1989), Glosten *et al.* (1993), and Nelson (1991)); for the remaining two, it is positive. While the explanations for observed negative correlations are provided in terms of leverage effect and volatility feedback, the same for the positive correlation is given in terms of time-varying risk premium theory.

Insofar as the risk aversion parameter δ is concerned, the findings are exactly the same as for the AR-GARCH-M model *viz.*, this parameter is insignificant for all the eight return series. Thus, the conclusion, based on these two benchmark models, is that there is no direct effect of risk on the expected return for all the eight series. Since the GARCH and EGARCH models are not nested, it cannot be formally tested if asymmetry in volatility represents a statistically better risk-return relationship. However, looking at the maximized log-likelihood values, it is noted that except for returns on Russia's stock market index MICEX, there is substantial improvement in the likelihood values for all other returns series, and, to that extent the AR-EGARCH-M model is a better model for returns than the AR-GARCH-M model.

3.3.2 Findings on the proposed models

We now consider the first proposed model *viz.*, the TAR-GARCH-M model where two regimes based on positive and non positive past average returns - called up and down market movements - are considered for the conditional mean model. As mentioned in Section 3.2, the two regimes - up and down - have been chosen based on the value of $\bar{r_t}^k$, the average of k past returns, being positive (> 0) and non-positive (≤ 0), respectively. As regards the choice of k, we have considered several values, especially because the data are at daily frequency. Thus , starting with $k = 5$, the values were considered with small gaps *viz.*, $k = 7$, 10, 15, 20, 25, 30 and finally with big jumps till up to $k = 150$ i.e., 50, 75, 100 and 150. For each of the choices, this model was estimated and that value of k was finally chosen for which the log-likelihood value was found to be the maximum. It may be noted that the maximized likelihood value was found to be almost the same for $k > 20$ for all the series. The values of k for the eight return series were thus obtained as 20 for returns on BOVESPA, SENSEX, SSE COMPOSITE, S&P 500, 15 for returns on MICEX, 10 for returns on FTSE ALL and 5 for returns on HANG SENG and NIKKEI 225.

Table 3.3: Estimates of the parameters of the TAR(1)-GARCH(1,1)-M model

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
μ_1	-0.0669	-0.0649	-0.0812	-0.09992	-0.2722	-0.2486	0.1304	-0.2708
	(0.40)	(0.31)	(0.37)	(0.41)	(0.13)	(0.11)	(0.22)	(0.01)
ϕ_1	-0.0867	-0.0311	-0.0155	-0.0177	-0.0098	0.0045	-0.0152	-0.0096
	(0.00)	(0.24)	(0.56)	(0.52)	(0.71)	(0.87)	(0.76)	(0.70)
δ_1	0.1116	0.1433	0.0928	0.1066	0.1920	0.1655	-0.0910	0.1838
	(0.13)	(0.03)	(0.22)	(0.25)	(0.07)	(0.04)	(0.37)	(0.03)
μ_2	0.0370	0.0566	0.0895	0.1759	-0.0767	0.3477	0.1528	0.0506
	(0.53)	(0.26)	(0.27)	(0.09)	(0.66)	(0.01)	(0.10)	(0.66)
ϕ_2	-0.0299	-0.0478	0.0430	0.0248	0.0239	0.0329	0.1712	0.0022
	(0.26)	(0.09)	(0.14)	(0.40)	(0.36)	(0.21)	(0.00)	(0.93)
δ_2	0.0012	-0.0256	-0.0343	-0.1261	0.1054	-0.1246	-0.1059	0.0187
	(0.98)	(0.69)	(0.63)	(0.14)	(0.35)	(0.13)	(0.22)	(0.83)
ω	0.0154	0.0136	0.0148	0.0448	0.0677	0.0947	0.0570	0.0293
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00	(0.00)	(0.00)	(0.00)
α	0.0868	0.1154	0.0670	0.1072	0.0727	0.1068	0.1314	0.0626
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9035	0.8784	0.9266	0.8759	0.9070	0.8739	0.8496	0.9259
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLLV	-4861.24	-4679.06	-5299.01	-5527.04	-6312.06	-6701.48	-5680.56	-5885.93

In Table 3.3, we specify the following models for r_t and h_t:

$$r_t = \begin{cases} \mu_1 + \phi_1 r_{t-1} + \delta_1\sqrt{h_t} + \varepsilon_{1t}, & \text{for down market} \\ \mu_2 + \phi_2 r_{t-1} + \delta_2\sqrt{h_t} + \varepsilon_{2t}, & \text{for up market} \end{cases} \qquad \varepsilon_t, |\psi_{t-1} \sim N(0, h_t)$$

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

The entries in parentheses are the $p-$ values; MLLV is the maximized log-likelihood value.

From the estimates of this model, which are presented in Table 3.3, it is noted that with the introduction of two regimes from consideration to market conditions and the resulting specification of the model for conditional mean, the findings are now found to be somewhat different. The autocorrelation coefficient for the down state, ϕ_1, is found to be significant only for S&P 500 returns, while for the other i.e., the up state, ϕ_2 is significant for India and the UK. The parameters of the GARCH model are found to be statistically significant for all the returns, as expectedly. As regards the two risk aversion parameters, δ_1 and δ_2, for the two mean regimes, δ_1 is found to be significant for returns on Brazil, Russia, China and the UK while δ_2 is insignificant for all stock markets. Thus, it is found that with introduction of regimes characterized by up and down movements of stock market in conditional mean and the time-varying risk being represented by GARCH, the expected return is found to be significantly influenced by (symmetric) volatility directly, unlike in the first two models. There is also some improvement, as compared to the AR-GARCH-M model, in terms of maximized log-likelihood value for most of the stock indices, thus suggesting that consideration of market conditions in mean model is useful. However, similar improvement does not occur if comparison is made with the AR-EGARCH-M model. This indicates that while volatility captured by the GARCH model is statistically valid, it is not the appropriate model for the volatility for all the series, and hence even with the introduction of market conditions, there is no improvement in terms of maximized log-likelihood values.

Therefore, we now consider the other two proposed models - TAR-EGARCH-M and STAR-EGARCH-M – the conditional mean specification of which are specified in equations (3.2) and (3.5), respectively, and the conditional variance is given by the EGARCH model (equation (3.4)) for both. Empirical results of these two models are presented in Tables 3.4 and 3.5, respectively. It is noted first that all the three parameters of the EGARCH model *viz.*, α, λ and β are significant as in case of the AR-EGARCH-M model. But the estimates of α is now negative for all the eight return series establishing thereby the presence of leverage effect in the returns of all eight stock markets considered in this study. The most significant observation, however, is that either of the two risk aversion parameters referring to the two market movements considered, δ_1 and δ_2, is significant for all but one return series i.e., those on BOVESPA, SENSEX, SSE COMPOSITE, S&P 500, FTSE ALL, HANG SENG and NIKKEI 225 stock indices. It is only for returns on MICEEX index of Russia that both δ_1 and δ_2 have been found to be significant. It is thus clearly established that the proposed TAR-EGARCH-M model is a better model in representing risk-return relationship since unlike the others models, at least one of the two risk aversion parameters is significant in all the eight return series.

Further, except for SENSEX of India, $\hat{\delta_1}$ has been found to be positive for all the remaining seven markets. Of these seven markets, δ_1 has been found to be statistically significant for five markets, and these are BOVESPA, MICEX, SSE COMPOSITE, S&P 500 and FTSE ALL. On the other hand, $\hat{\delta_2}$ has been found to be negative for all but one (which is BOVESPA of Brazil) return series. In case of δ_2, four return series *viz.*, MICEX, SENSEX, HANG SENG and NIKKEI 225, have been found to be significant. In terms of the two regimes characterized by two different market conditions – up and down - these findings suggest that response of risk (as measured by conditional variance) to these two market conditions is asymmetric since we have found that in the down market, which is the unfavourable market, expected return is higher in direct response to higher volatility while for up market, higher risk has been found to lead to lower expected return. Thus, not only that the risk aversion parameter is now found to be significant in one or both the market movements, but also that its signs for these two market conditions have been found to be different - positive for down market and negative for up market, as expected. The empirical findings also show that there is no substantial difference in the nature of the risk-return behaviour of investors belonging to advanced and BRIC countries from consideration of up and down markets.

Table 3.4: Estimates of the parameters of the TAR(1)-EGARCH(1,1)-M model

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
μ_1	-0.3081	-0.1548	-0.1012	-0.1062	-0.6719	-0.3300	0.0712	-0.3025
	(0.00)	(0.02)	(0.28)	(0.38)	(0.00)	(0.02)	(0.49)	(0.00)
ϕ_1	-0.0821	-0.0248	-0.0254	-0.0328	0.0041	-0.0035	-0.0107	-0.0096
	(0.00)	(0.36)	(0.35)	(0.29)	(0.88)	(0.90)	(0.84)	(0.70)
δ_1	0.1940	0.1134	0.0551	0.0558	0.3242	0.1694	-0.0916	0.1810
	(0.00)	(0.07)	(0.45)	(0.53)	(0.00)	(0.01)	(0.36)	(0.02)
μ_2	0.0793	0.0420	0.1898	0.2001	0.0338	0.3551	0.2209	0.1087
	(0.10)	(0.35)	(0.01)	(0.04)	(0.83)	(0.00)	(0.01)	(0.31)
ϕ_2	-0.0270	-0.0448	0.0514	0.0292	0.0423	0.0233	0.1926	-0.0023
	(0.27)	(0.07)	(0.06)	(0.30)	(0.08)	(0.32)	(0.00)	(0.93)
δ_2	-0.0711	-0.0120	-0.1372	-0.1976	0.0232	-0.1586	-0.2142	-0.0155
	(0.24)	(0.84)	(0.06)	(0.02)	(0.82)	(0.02)	(0.01)	(0.85)
ω	0.0032	-0.0012	0.0099	0.0223	0.0336	0.0450	0.0300	0.0188
	(0.25)	(0.66)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α	-0.1446	-0.1365	-0.0672	-0.1023	-0.1020	-0.0502	-0.1045	-0.0268
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
λ	0.0789	0.1145	0.1251	0.1830	0.1126	0.2209	0.2422	0.1262
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9817	0.9814	0.9870	0.9690	0.9698	0.9719	0.9629	0.9863

Continued on next page

Table: 3.4 *Continued from previous page*

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLLV	-4776.91	-4603.54	-5493.29	-5488.42	-6274.59	-6704.54	-5655.56	-5877.22

In Table 3.4 , we specify the following models for r_t and h_t:

$$r_t = \begin{cases} \mu_1 + \phi_1 r_{t-1} + \delta_1 \sqrt{h_t} + \varepsilon_{1t}, & \text{for down market} \\ \mu_2 + \phi_2 r_{t-1} + \delta_2 \sqrt{h_t} + \varepsilon_{2t}, & \text{for up market} \end{cases} \qquad \varepsilon_t, |\psi_{t-1} \sim N(0, h_t)$$

$$\ln h_t = \omega + \alpha \left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}} \right) + \lambda \left[|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}| - \sqrt{\frac{2}{\pi}} \right] + \beta \ln h_{t-1}.$$

The entries in parentheses are the $p-$ values; MLLV is the maximized log-likelihood value.

The estimates of the last model considered *viz.*, the STAR-EGARCH-M are presented in Table 3.5. This model is different from the TAR-EGARCH-M model in that now there is a smooth transition mechanism from one market condition to the other through the assumption of logistic function. The two models are otherwise the same. It is obvious from the entries in this table that the empirical results including the maximized log-likelihood values are almost the same as those for the TAR-EGARCH-M model for each of the eight stock returns. The estimate of γ , the parameter of smoothness in the logistic transition function, has been found to be very high for all the stock returns except for returns on SENSEX of India and SSE COMPOSITE of China. As already stated in Section 3.2, under this condition, the transition is almost instantaneous at $\bar{r}_t^k = 0$, and hence the STAR model for conditional mean reduces to the TAR model. Accordingly, no further discussions of the findings of this model are made.

Table 3.5: Estimates of parameters of the STAR(1)-EGARCH(1,1)-M model

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
μ_1	-0.3079	-0.1747	-0.1152	-0.1090	-0.6769	-0.3281	-0.0402	-0.3761
	(0.00)	(0.01)	(0.18)	(0.36)	(0.00)	(0.02)	(0.84)	(0.00)
ϕ_1	-0.0830	-0.0232	-0.0264	-0.0329	0.0035	-0.0028	-0.0587	-0.0132
	(0.01)	(0.41)	(0.36)	(0.28)	(0.90)	(0.92)	(0.49)	(0.60)
δ_1	0.1910	0.1249	0.0647	0.0580	0.3241	0.1677	-0.0743	0.2183
	(0.00)	(0.05)	(0.35)	(0.51)	(0.00)	(0.01)	(0.58)	(0.01)
μ_2	0.0778	0.0513	0.2063	0.1971	0.0184	0.3467	0.3913	0.1505

Continued on next page

Table: 3.5 Continued from previous page

	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
	(0.10)	(0.26)	(0.01)	(0.04)	(0.91)	(0.00)	(0.06)	(0.21)
ϕ_2	-0.0261	-0.0454	0.0582	0.0279	0.0436	0.0240	0.1409	0.0036
	(0.30)	(0.07)	(0.05)	(0.33)	(0.09)	(0.30)	(0.07)	(0.88)
δ_2	-0.0688	-0.0234	0.1538	-0.1939	0.0350	-0.2426	-0.2426	-0.0278
	(0.25)	(0.70)	(0.03)	(0.02)	(0.73)	(0.03)	(0.04)	(0.75)
ω	0.0032	-0.0011	0.0098	0.0223	0.0339	0.0450	0.0302	0.0188
	(0.20)	(0.68)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
α	-0.1453	-0.1374	-0.0675	-0.1023	-0.1030	-0.0503	-0.1048	-0.0289
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
λ	0.0785	0.1130	0.1248	0.1830	0.1126	0.2208	0.2427	0.1255
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
β	0.9817	0.9815	09871	0.9689	0.9694	0.9719	0.9629	0.9862
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
γ	45.13	26.36	13.70	500.01	18.85	341.57	1.50	0.71
	(0.38)	(0.37)	(0.36)	(0.49)	(0.42)	(0.47)	(0.13)	(0.12)
MLLV	-4776.62	-4602.72	-5492.66	-5488.53	-6274.42	-6704.76	-5654.43	-5875.64

In Table 3.5, we specify the following models for r_t and h_t:

$$r_t = (\mu_1 + \phi_1 r_{t-1} + \delta_1\sqrt{h_t})(1 - G(\bar{r_t}^k;\gamma,c)) + (\mu_2 + \phi_2 r_{t-1} + \delta_2\sqrt{h_t})(G(\bar{r_t}^k;\gamma,c)) + \varepsilon_t, \qquad \varepsilon_t|\psi_{t-1} \sim N(0,h_t)$$

$$G(\bar{r_t}^k;\gamma,c) = \frac{1}{1+\exp(-\gamma[\bar{r_t}^k - c])}$$

$$\ln h_t = \omega + \alpha\left(\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}\right) + \lambda\left[|\frac{\varepsilon_{t-1}}{\sqrt{h_{t-1}}}| - \sqrt{\frac{2}{\pi}}\right] + \beta\ln h_{t-1}.$$

Values in parentheses are the $p-$ values; MLLV is the maximized log-likelihood value.

3.4 Findings on Tests of Hypotheses

We first carried out the Ljung-Box test $Q(\cdot)$ with both standardized residual and squared standardized residuals for all the five models in order to find if the chosen lag values of the models for both the conditional mean and conditional variance were adequate. The values of this test statistic are presented in Table 3.6 for the proposed TAR-EGARCH-M model only[5]. It is quite evident from this table that the chosen lag value of unity for the conditional mean is adequate for all the eight return series since the

[5]The test statistic values are almost the same for the other proposed model i.e., the STAR-EGARCH-M model and hence these are not reported. As for the other models, the conclusions are, by and large, the same.

test statistic values suggest that the null hypothesis of 'no autocorrelation in standardized errors' cannot be rejected. As regards the adequacy of the orders (1,1) for the conditional variance model EGARCH, it is noted that at 1% level of significance, the $Q^2(\cdot)$ values indicate that the null hypothesis of 'no autocorrelation in squared standardized errors' is rejected for returns on stock indices of Russia, the US and Hong Kong. In case of Brazil, the same null hypothesis is rejected at 5% level of significance. For the remaining four series, the choice of the order was found to be adequate.

Table 3.6: $Q(\cdot)$ and $Q^2(\cdot)$ values for the residuals of the TAR(1)-EGARCH(1,1)-M model

Cnty. / Stat.	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
$Q(5)$	9.1276	6.0071	8.3223	0.8842	4.4053	5.1346	8.1960	6.4387
	(0.10)	(0.31)	(0.14)	(0.89)	(0.49)	(0.40)	(0.15)	(0.26)
$Q(10)$	13.9194	8.6823	11.0464	7.6421	8.3952	10.3242	16.4307	22.7153
	(0.18)	(0.56)	(0.35)	(0.66)	(0.59)	(0.41)	(0.09)	(0.01)
$Q^2(5)$	26.0054	1.6951	19.4491	7.1519	12.5082	19.4176	4.0754	3.0411
	(0.00)	(0.89)	(0.00)	(0.21)	(0.03)	(0.00)	(0.53)	(0..69)
$Q^2(10)$	42.2025	9.4082	29.3843	9.9140	19.9892	21.2706	8.3980	5.0272
	(0.00)	(0.49)	(0.00)	(0.45)	(0.03)	(0.01)	(0.59)	(0.89)

Note: $p-$values are given in parentheses.

Summing up the empirical findings so far, we can state that consideration to stock market movements like up and down in specifying the conditional mean model along with asymmetry in the sense of leverage effect in specifying the conditional variance model, are very important in proper modelling of risk-return relationship where time-varying risk is assumed to directly affect the conditional mean. As noted in the Table 3.1 through 3.5, in terms of maximized log likelihood values substantial gains are made in the model hierarchy considered in this paper *viz.*, starting with the AR-GARCH-M where there is no regime in conditional mean as well as no asymmetry in volatility, the modelling performance improves when asymmetry in conditional variance only is considered. The performance of the TAR-EGARCH-M model shows that in all return series, EGARCH, rather than GARCH, is the appropriate model for volatility. The proposed models i.e., the TAR-EGARCH-M and STAR-EGARCH perform almost the same suggesting thereby that there is no smooth transition from one market state to the other. Further, these two models perform superior to all other models considered in terms of maximized log-likelihood values.

In order to find if the proposed TAR-EGARCH-M (also the STAR-EGARCH-M) model performs significantly better than the benchmark model AR-EGARCH-M, we carried out the likelihood ratio test, and found, as shown in Table 3.7, that the proposed model is significantly better for all the markets with the sole exception of the stock market of Japan.

Table 3.7: Likelihood ratio test statistic values

Country	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
H_1 / H_0	TAR-EGARCH-M							
AR-EGARCH-M	28.23	6.45	8.62	3.57	19.19	15.42	10.71	33.01
	(0.00)	(0.09)	(0.03)	(0.31)	(0.00)	(0.00)	(0.01)	(0.00)

Note: $p-$values are given in parentheses.

The most important hypothesis of interest for the proposed models is whether risk responds to returns differently in the up and down market movements or not. In terms of the parameters, the null and alternative hypotheses are $H_0 : \delta_1 = \delta_2$ and $H_1 : \delta_1 \neq \delta_2$, respectively. This null hypothesis has been tested by using the Wald test and the statistic values are given in Table 3.8 for the TAR-EGARCH-M model[6]. Before testing this null hypothesis, we first tested the null hypothesis $\mu_1 = \mu_2, \phi_1 = \phi_2, \delta_1 = \delta_2$ in order to infer if introduction of the two states of market is at all statistically tenable. The Wald test statistic values for this null hypothesis are also presented in Table 3.8. It is evident from this table that this null hypothesis is rejected for all the eight return series, thus empirically supporting the introduction of two market states for the conditional mean model. To be more specific, this finding suggests that the two market situations indeed require two different conditional mean models. Now, to find whether rejection of this null hypothesis is due to differences in autocorrelation coefficient values only, we also tested the null hypothesis given as $\phi_1 = \phi_2$. This hypothesis was found to be ‘not rejected’ in all but two return series. These two exceptions are the returns on SENSEX of India and HANG SENG of Hong

[6]The test statistic values in case of the STAR-EGARCH-M model are almost the same and hence these are not reported separately.

Kong. It may be worth recalling that ϕ_1 and /or ϕ_2 were found to be statistically significant only in case of few stock returns. Finally, the results of the Wald test for $H_0 : \delta_1 = \delta_2$ show that this null hypothesis is rejected in all but returns on SENSEX and FTSE ALL. Thus, it can be inferred that except for these two stock indices, the relative risk aversion parameters in the two market conditions are different for the other six return series *viz.*, BOVESPA, MICEX, SSE COMPOSITE, S&P 500, HANG SENG and NIKKEI 225. This empirically establishes the fact that investors' reaction to returns in response to risk are different in these two states of market characterized by up and down movements, and that this is regardless of the fact whether the stock market is from an advanced economy or form an important emerging economy called the BRIC group.

Table 3.8: Results of the Wald test for the TAR(1)-EGARCH(1,1)-M model

H_0 \ Country	The US	The UK	Hong Kong	Japan	Brazil	Russia	India	China
$\mu_1 = \mu_2, \phi_1 = \phi_2, \delta_1 = \delta_2$	48.9482	12.4868	11.9175	7.3422	27.1837	17.3195	12.0445	22.0121
	(0.00)	(0.01)	(0.01)	(0.06)	(0.00)	(0.00)	(0.01)	(0.00)
$\phi_1 = \phi_2$	2.0035	0.2758	3.4002	2.1367	0.9026	0.4838	8.9617	0.0432
	(0.15)	(0.59)	(0.07)	(0.14)	(0.34)	(0.48)	(0.00)	(0.83)
$\delta_1 = \delta_2$	14.3499	2.2395	3.7520	4.1912	5.7236	11.6848	0.9487	3.3650
	(0.00)	(0.13)	(0.06)	(0.04)	(0.02)	(0.00)	(0.33)	(0.07)

Note: $p-$values are given in parentheses.

3.5 Concluding Remarks

In this chapter, univariate models for stock returns at daily frequency have been proposed for studying the risk-return relationship in the framework where (i) risk directly affects returns, as in the GARCH-in-mean model, (ii) two stock market movements, called the up and down markets - based on past returns, are incorporated in the conditional mean returns model, and (iii) the risk aversion parameter is taken to be different so that it can be investigated if risk responds differently in the two market situations. The specification of the conditional variance has been taken to be the EGARCH model which takes into account the leverage effect which defines the asymmetric behaviour of return shocks on conditional variance. The two models capturing this features, designated as the TAR-EGARCH-M and STAR-EGARCH-M models, differ only in respect of the fact that the logistic transition function is considered for smooth transition from one regime to the other in case of the latter model. Returns from the eight stock indices - four from developed economies and four from important emerging economies - have been used to estimate the proposed models along with two benchmark models where the two different market movements - up and down - have not been considered.

The empirical findings are overwhelmingly in favour of the proposed models - the TAR-EGARCH-M and STAR-EGARCH-M models. It is found that the mean return regimes referring to up and down markets are statistically valid for all the eight return series. Further and more importantly, risk in terms of time-varying conditional variance is found to respond 'asymmetrically' in the two market conditions in the sense that the risk aversion parameter has been found to be positive in case of down market and negative for up market. These empirical findings thus give support to the observations made by Fabozzi and Francis (1977) and Kim and Zumwalt (1979) that investors require a premium for taking downside risk and pay a premium for upside variation. Finally, it is also observed that modelling consideration to stock market conditions through the introduction of regimes, yields a statistically better model since the AR-EGARCH-M model is found to be rejected, by the likelihood ratio test, in favour of the proposed TAR-EGARCH-M model for all stock markets except that of Japan.

Chapter 4

Threshold VAR - Bivariate Threshold GARCH-in-Mean Model: The BEKK Approach

4.1 Introduction

The analysis of international financial system and the interconnection of markets have become major topics of research in financial econometrics in recent years. The availability of daily data and the connectedness of financial markets have inspired analysis of the transmission mechanism of different stock markets. Studying the transmission of movements of stock markets is a joint study of the spillover of prices and the volatility of prices. Ultimately, it is the perceived importance of the information contained in price movements of other markets that influences investors in the market to which the spillover occurs. With the increasing integration of the major financial markets around the world, studies on the transmission of stock return movements among the major markets have gained momentum and become important. Evidence of spillovers and volatility transmissions from one market to another is now well established (see, among others, Engle *et al.*(1990), and Hamao *et al.* (1990)). In this context, mention may be made of the study by Eun and Shim (1989) who applied the vector autoregressive (VAR) model to daily market index data in a study of the transmission of stock return movements among the nine largest stock markets in the world, and found a substantial amount of multilateral interactions among the markets. Joen and Von Frustenberg (1990), also using the VAR methodology, found evidence of growing international integration of four major equity markets. More recent studies on financial crises and contagion provide further evidence that there is significant transmission across markets. For instance, Kaminsky and Reinhart (1998), and Bae *et al.* (2003) have documented existences of mean and volatility spillovers between asset markets and also the empirical fact that the magnitude of such interrelationships may be strengthen during crisis periods. Examining the nature of volatility spillovers from Japan and the US to the Pacific-Basin under the impact of financial liberalization of the latter countries, Ng (2000) found that both the US and Japan influence volatility in the Pacific-Basic region. Worthington and Higgs (2004) have provided evidence of the transmission of returns and volatility among nine developed and emerging Asia-Pacific markets with the US uncovering contemporaneous return and volatility linkages which intensified after the Asian crisis.

Beginning with the work of Kyle (1985), several studies have indicated that much of the information would be revealed in the volatility of stock prices rather than the price itself. Given the interpretation of shocks as news and the fact that at least certain news items affect various stock markets simultaneously, it is suggested and, in fact, widely accepted that financial volatilities move together over time across markets. Recognising this feature through a multivariate modelling framework leads to more relevant empirical models than working with separate univariate models since in case of multivariate models, it is possible to exploit the possible linkages that exist. An alternative motivation for multivariate models is that the covariances among the assets play a crucial role in the decision problem on portfolios, since construction of portfolios from various financial assets play a major role in financial economics, and multivariate GARCH models can be used to model the time-varying behaviour of these conditional covariances. In this context, mention may be made of the work by King and Wadhwani (1990) who examined the contagion effect between two countries using three data sets on fifteen-minutes' index returns on stock indices of New York, London and Tokyo stock markets. In this work, the underlying volatility of each return series has been taken to be its variance and hence the volatility considered is not time-varying. However, as it is well-known, stock returns data display volatility clustering, which, in other words, means that the volatility of returns is time-varying. Given this fact, application of the VAR model which, in general, assumes time-invariant conditional variance for studying the transmission of stock price movements would not allow study of all aspects of transmission of movements of stock returns.

Thus, to study the relationships involving volatilities and co-volatilities of several markets, multivariate GARCH (MGARCH) models are used. In their survey paper on MGARCH models, Bauwens *et al.* (2006) have clearly stated that MGARCH models provide answer to the following questions: (i)

Does a shock in a stock market increase the volatility of another market, and if so, by how much? (*ii*) Is the volatility of a stock market transmitted to another directly (through its conditional variances) and indirectly (through its conditional covariances)? (*iii*) Is the impact the same for negative and positive shocks of the same amplitude? A related issue is whether the correlation between the returns changes over time. Further, are these higher during the period of higher volatility? Are these increasing in the long run, perhaps because of the globalization of financial markets? Such issues can be studied directly by using MGARCH models, and obviously these would involve specifications of the dynamics of covariances or correlations.

The presence of asymmetric volatility, most often interpreted as the leverage effect, is quite a common feature with stock returns and it is most apparent during stock market crashes when a large decline in stock price is associated with a significant increase in market volatility. As mentioned in Chapter 3, univariate models that allow for this effect are the EGARCH model of Nelson (1991) and the threshold GARCH (TGARCH) model, originally due to Zakoian (1991) and later a similar formulation, known as the GJR GARCH model, by Glosten *et al.* (1993). In case of multivariate returns series, the same argument for the leverage effect applies *viz.*, the variances and the covariances may react differently to a positive shock than to a negative shock. Unlike the univariate case, models capturing the leverage effect in the multivariate case and their subsequent applications are only very few. Kroner and Ng (1998) proposed the asymmetric dynamic covariance model while Hansson and Hordahl (1998) and Hafner and Herwartz (1998) suggested some additional terms to the usual MGARCH model so as to capture this effect. Very recently, Griel *et al.* (2004) have extended the BEKK representation of MGARCH model, originally due to Baba, Engle, Kraft and Kroner (1990), to incorporate leverage effect in the MGARCH set-up. It may be worthwhile to note that Bollerslev *et al.* (1988) carried out one of the first multivariate analyses in a test of CAPM where expected returns were assumed to depend on the time-varying covariance matrix of asset returns of three assets *viz.*, US bonds, bills and stocks. Bekaert and Wu (2000) examined asymmetric volatility in the Japanese equity market using a general empirical framework based on a multivariate GARCH-in-mean model. They also tried to differentiate between the two main explanations for the asymmetry, and concluded that volatility feedback was the dominant cause for asymmetry of returns on Japanese stock market. Similar studies were carried out on all common stocks traded on the New York stock exchange by Ng (1991), and also on industry portfolios on the New York and American Stock Exchange by Engel *et al.* (1995). Hall *et al.* (1989) also studied the issue of asymmetry in volatility in multivariate framework on four industry portfolios on the London

Stock Exchange. Multivariate extensions of the univariate asymmetric conditional variance models have also been proposed by Koutmos and Booth (1995) and Braun *et al.* (1995).

On the issue of 'asymmetry' in conditional mean, or where the effect of risk on stock returns is different in different market movements like up and down markets, it has been stated in Chapter 3 that even in case of univariate time series, models which allow for such market behaviours are very few and that too very recent. To the best of our knowledge, in the multivariate case, there is hardly any study allowing for different effects of risk on returns being different due to different market movements. Such studies in multivariate framework entails links across several markets. Empirical modelling of such links is relevant for trading and hedging strategies, and these links provide insights into the transmission of shocks (news) across stock markets of different countries. Further, it helps to study spillovers from one stock market to another in mean returns and volatility along with cross-market linkages. It is also noteworthy that the generalization of GARCH-in-mean model for the univariate case is very meaningful in studying risk-return relationship in the multivariate case as well. As it is, there are only very few studies with multivariate GARCH-in-mean (MGARCH-M) model involving different financial variables. However, to the best of our knowledge, there is only one paper with returns data on stock markets (*cf.* Beirne *et al.*(2009)) where trivariate GARCH-in-mean model has been used to study global and regional spillovers in emerging markets, and there is no paper where asymmetry in conditional variance has been considered in MGARCH-M modelling framework. The approach considered in Beirne *et al.* builds and expands on the methodologies adapted in earlier studies such as Hamao *et al.* (1990), Ng (2000) and Bekaert *et al.* (2005). Although with the recent advances in multivariate time series econometric modelling, interdependences in terms of both first and second order moments of returns distributions are being studied, and to that extent the usual MGARCH models are increasingly being applied recently (see, Savva (2012) *etc.*, for details), yet extensions of the usual MGARCH models in the directions mentioned above are really very limited.

In this chapter, we propose a model in MGARCH-M framework where asymmetry in conditional variance and different effects of up and down markets on conditional mean are duly incorporated. This is essentially a generalization of the TAR-EGARCH-M model of Chapter 3 in the multivariate case. The issue of extension of univariate to multivariate is due to consideration to several stock markets being taken together for the purpose of more appropriate models where different kinds of spillover effects, as already mentioned in previous paragraphs, can be studied. One important practical limitation of such models is the large number of parameters involved, and hence these models are usually studied with 2/3 variables (in our case, stock returns) taken together. As in the univariate case, we take the same eight countries - four advanced stock markets (the USA, the UK, Hong Kong and Japan) and four important emerging economies, also called the BRIC group of countries (Brazil, Russia, India and China) - for this study. The reasons behind choosing such a group of countries have already been stated in Chapter 2. It is also a fact that research into asset market linkages and integration in both developed and emerging markets have gained momentum over recent years establishing the nature of these relationships for different asset markets. As a consequence of the Asian financial crisis, the majority of studies have focused on emerging stock markets in the Pacific-Basin (see, in this context, Phylaktis and Ravazzolo (2002), and Manning (2002)), although there is evidence of such linkages and integration involving some other emerging economies as well (*cf.* Bekaert and Harvey (1995,1997)). Now, from consideration of the issue of large number of parameters involved, the actual study is done separately for all possible pairs of stock returns on these eight stock markets. In other words, we apply the models in the bivariate set-up only. Here the BEKK representation of the well known MGARCH model, proposed by Engle and Kroner (1995), is considered while the dynamic conditional correlation approach is discussed in the next chapter.

The chapter is organized as follows. The proposed model along with some existing models are presented in the next section. Section 4.3 outlines the estimation and tests of hypotheses. In Section 4.4, the empirical results on estimation of the models are discussed. The findings on the tests of hypotheses are presented in Section 4.5. This chapter ends with some concluding remarks in Section 4.6.

4.2 The Proposed Model

In this section, we present the model proposed for the multivariate case from modelling considerations mentioned in the preceding section. In order to do that we first state the standard MGARCH model, more particularly, the BEKK specification of MGARCH model.

4.2.1 The BEKK representation

The general framework of an MGARCH model conditional on the $\sigma-$field generated by the past information on r_t up to time $t-1$ and denoted by ψ_{t-1}, is specified as

$$r_t = \mu_t(\theta) + \varepsilon_t \tag{4.1}$$

where r_t is an $N \times 1$ vector of returns at time t on N stock indices of N countries, $\mu_t(\theta)$ is the $N \times 1$ conditional mean vector, $\varepsilon_t = H_t^{1/2}(\theta)\eta_t$, η_t is an $N \times 1$ random vector with $E(\eta_t) = 0$, $V(\eta_t) = I_N$, I_N is the identity matrix of order N, and θ is a finite vector of parameters. Further, $H_t^{1/2}(\theta)$ is assumed to be an $(N \times N)$ positive definite matrix such that $H_t(\theta)$ is the conditional variance-covariance matrix of r_t. Both $H_t(\theta)$ and $\mu_t(\theta)$ depend on the unknown vector θ. Under this assumption on $H_t^{1/2}(\theta)$, $H_t(\theta)$ is also a positive definite matrix.

In the literature on MGARCH model, there are primarily three non-mutually exclusive approaches. These are: *(i)* direct generalization of the univariate GARCH model of Bollerslev (1986), *(ii)* linear combinations of the univariate GARCH models, and *(iii)* nonlinear combinations of univariate GARCH models. The models in the first category are known as VEC, BEKK and factor models. The models under the second category are the orthogonal models and latent factor models while those under *(iii)* are constant and dynamic conditional correlation models, the general dynamic covariance model and the copula GARCH model (see, Bauwens *et al.* (2006), for an excellent survey on MGARCH model and its various extensions and generalizations). In this chapter we consider primarily the BEKK specification of MGARCH model.

Two most important issues for MGARCH models are: *(i)* ensuring the positive definiteness property of $H_t^{1/2}$ or, for that matter of[1] H_t and *(ii)* dealing with a large number of parameters involved, which makes it very difficult to estimate the parameters of the models in practice. It may be noted that in case of general VEC model, each element of H_t is a linear function of the lagged squared errors and cross-products of errors and lagged values of the elements of H_t. The number of parameters in this model is $N(N+1)(N(N+1)+1)/2$, the value of which is 78 for $N = 3$. Thus, even for a trivariate VEC model the number of parameters is indeed very large. Further, it is difficult to guarantee the positive definiteness of H_t in the VEC model without imposing strong restrictions on the parameters (see, Gourieroux (1997)for sufficient conditions for the positive definiteness of H_t). Hence, keeping these two conditions in mind, we have considered, in this chapter, the BEKK model for incorporating volatility dependences across different return series. Engle and Kroner (1995) proposed a new parametrization for H_t that easily imposes the positive definiteness restriction *viz.*, the BEKK model which is originally due to Baba, Engle, Kraft and Kroner (1990). The BEKK (1,1,1) model is given as:

$$H_t = \mathcal{C}\mathcal{C}' + \mathcal{A}\varepsilon_{t-1}\varepsilon_{t-1}'\mathcal{A}' + \mathcal{B}H_{t-1}\mathcal{B}' \tag{4.2}$$

where $\mathcal{C}$, $\mathcal{A}$ and $\mathcal{B}$ are $N \times N$ matrices each but $\mathcal{C}$ is upper triangular. The number of parameters

[1] Henceforth, the argument θ is being dropped from $H_t(\theta)$ for the sake of notational simplicity.

in BEKK(1,1,1) is $N(5N+1)/2$ which is 24 when $N=3$, and thus the number is greatly reduced as compared to the VEC model. It may be noted, in this context, that the BEKK model is a special case of the VEC model, and that its parameters do not represent directly the impacts of the different lag terms of the elements of H_t. Further, the BEKK parametrization guarantees H_t to be positive definite for all values of ε_t in the sample.

4.2.2 The proposed TVAR- BTGARCH-M model

As stated in Section 4.1, one important aspect of the proposed model is that it considers the risk-return relationship in the MGARCH-in-mean framework so that the direct effect of current volatility in determining current expected returns could be captured. Thus the conditional mean specification is taken to have a VAR(1)[2] representation along with a vector representing the 'in-mean' component. Hence, the model for r_t of order $N \times 1$ is

$$r_t = a + Br_{t-1} + \Lambda \text{vech}^3(H_t) + \varepsilon_t, \qquad \varepsilon_t|\psi_{t-1} \sim \text{multivariate Normal } (0, H_t) \tag{4.3}$$

where a is an $N \times 1$ vector, B is an $N \times N$ matrix of parameters associated with r_{t-1}, and Λ is an $N \times N(N+1)/2$ matrix whose elements stand for own risk aversion parameters as well as cross market risk aversion parameters. As mentioned in the preceding section, this study is at bivariate level, i.e., $N=2$, and hence, all subsequent representations are being stated taking $N=2$. Accordingly, the vectors and matrices involved in this model, in terms of their elements, are the following:

$$r_t = \begin{pmatrix} r_{1t} \\ r_{2t} \end{pmatrix}, \; a = \begin{pmatrix} a_1 \\ a_2 \end{pmatrix}, \; B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, \; \mathcal{C} = \begin{pmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{pmatrix}, \; \mathcal{A} = \begin{pmatrix} \alpha_{11} & \alpha_{12} \\ \alpha_{21} & \alpha_{22} \end{pmatrix}, \; \mathcal{B} = \begin{pmatrix} \beta_{11} & \beta_{12} \\ \beta_{21} & \beta_{22} \end{pmatrix},$$

$$\Lambda = \begin{pmatrix} \lambda_{11} & \lambda_{12} & \lambda_{13} \\ \lambda_{21} & \lambda_{22} & \lambda_{23} \end{pmatrix}, \; H_t = \begin{pmatrix} h_{11t} & h_{12t} \\ h_{12t} & h_{22t} \end{pmatrix}, \; \text{vech}(H_t) = \begin{pmatrix} h_{11t} \\ h_{12t} \\ h_{22t} \end{pmatrix} \text{ and } \varepsilon_t = \begin{pmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{pmatrix}.$$

Noting that like the GARCH model in the univariate case, the BEKK model is symmetric in nature in that it does not capture the asymmetry in volatility of stock returns, which has been widely documented in the literature. Now, as outlined in Section 4.1, the study incorporates asymmetry in conditional variance, and hence we have taken the asymmetric version of the BEKK(1,1,1) representation, due to

[2] The order of VAR has been taken to be 1 all throughout since this choice was found to be adequate, by and large, for all the models considered in this chapter.

[3] 'vech' notation stands for a column vector of stacked lower triangular elements of a symmetric martix.

Grier *et al.* (2004), which is given as

$$H_t = \mathcal{C}\mathcal{C}' + \mathcal{A}\varepsilon_{t-1}\varepsilon'_{t-1}\mathcal{A}' + \mathcal{D}u_{t-1}u'_{t-1}\mathcal{D}' + \mathcal{B}H_{t-1}\mathcal{B}' \tag{4.4}$$

where $\mathcal{D} = \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix}$ is a 2×2 matrix of coefficients associated with u_{t-1} where $u_{t-1} = \begin{pmatrix} u_{1\overline{t-1}} \\ u_{2\overline{t-1}} \end{pmatrix}$ and $u_{i\overline{t-1}} = \varepsilon_{i\overline{t-1}} I(\varepsilon_{i\overline{t-1}} \leq 0)$, $i = 1, 2$, where $I(.)$ is an indicator function which takes the value 1 if $\varepsilon_{i\overline{t-1}} \leq 0$ and 0 otherwise. This generalization of H_t of the symmetric BEKK parametrization by incorporating asymmetry in conditional variance, henceforth to be called as the bivariate threshold GARCH (BTGARCH) model, is in line with GJR GARCH model by Glosten *et al.* (1993). The symmetric BEKK model is a special case of the model specified in equation (4.4) where $d_{ij} = 0$ for $i, j = 1, 2$.

The specification in equation (4.4) allows past volatilities captured through H_{t-1} as well as through $\varepsilon_{t-1}\varepsilon'_{t-1}$ and $u_{t-1}u'_{t-1}$ to show up in the current volatilities of the stock returns in two markets. Moreover, the $u_{t-1}u'_{t-1}$ term extends the BEKK model by relaxing the assumption of symmetry, thereby allowing for different relative responses to positive and negative shocks in the conditional variance-covariance matrix.

As regards capturing the two different market movements - up and down- in conditional mean, we have taken the TAR model in the bivariate case, and the threshold variable has been taken, as in Chapter 3, to be $\bar{r}^k_{1t}$ and $\bar{r}^k_{2t}$ for the two returns series, where $\bar{r}^k_{it}$ is the average of the past k returns on the i^{th} stock market ($i = 1, 2$) and the threshold value has been taken to be zero for both the returns. The two-regime TAR(1) model for bivariate case, denoted as TVAR(1), is written as:

$$r_t = (a^1 + B^1 r_{t-1}) \odot (\mathbf{1} - \boldsymbol{I}[\cdot]) + (a^2 + B^2 r_{t-1}) \odot \boldsymbol{I}[\cdot] + \varepsilon_t \tag{4.5}$$

where $a^i = \begin{pmatrix} a^i_1 \\ a^i_2 \end{pmatrix}$, $B^i = \begin{pmatrix} b^i_{11} & b^i_{12} \\ b^i_{21} & b^i_{22} \end{pmatrix}$ for $i = 1, 2$, $\mathbf{1} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$, $\boldsymbol{I}[\cdot] = \begin{pmatrix} I(\bar{r}^k_{1t}) \leq 0 \\ I(\bar{r}^k_{2t} \leq 0) \end{pmatrix}$, and $\boldsymbol{I}[\cdot]$ is the usual indicator function which takes the value 1 if $\bar{r}^k_{it} \leq 0$ ($i = 1, 2$) and 0 otherwise, and $\odot$ denotes the Hadamard product of matrices. Taking this specification of r_t specified in equation (4.5), we have the final form of the proposed model for r_t in the 'TGARCH-in-mean' framework as:

$$\begin{aligned} r_t &= \left(a^1 + B^1 r_{t-1} + \Lambda^1 \text{vech}\,(H_t)\right) \odot (\mathbf{1} - \boldsymbol{I}[\cdot]) \\ &\quad + \left(a^2 + B^2 r_{t-1} + \Lambda^2 \text{vech}\,(H_t)\right) \odot \boldsymbol{I}[\cdot] + \varepsilon_t \end{aligned} \tag{4.6}$$

where the conditional variance-covariance matrix, H_t, is given in equation (4.4). This model is designated as the threshold VAR- bivariate threshold GARCH -in-mean (TVAR-BTGARCH-M) model. Conditions for stationarity, as obtained by Chan and Tong (1985) and Chan *et al.* (1985) for the univariate TAR model, are assumed to hold for both the returns series separately.

In case H_t is as given in equation (4.2) i.e., H_t is the symmetric BEKK model, then the conditional variance is just the bivariate GARCH and it is termed as TVAR-BGARCH-M model. While this is also a new model since it incorporates the different effects of up and down states of the stock markets in the conditional mean with H_t being symmetric, there are three other models which are special cases of the proposed model. These are: VAR-BGARCH, VAR-BGARCH-M, and VAR-BTGARCH-M models. Since there is hardly any studies with these models, particularly the last two, even with returns data for developed stock markets, not to talk of emerging economies considered in this study, we consider these models as well in this chapter. Thus, starting with the usual VAR-BGARCH model which is being taken as the benchmark model, consideration of these models enables us to study how the performances of the models improve as characteristics like asymmetry in returns and different market movements are gradually incorporated in the models, finally leading to the proposed model given in equation(4.6).

4.3 Estimation and Hypothesis Testing

In this section, the estimation of the proposed TVAR-BTGARCH-M model is first discussed, although very briefly. Thereafter the different hypotheses of interest are stated.

4.3.1 Estimation

Given a sample of T observations and under the assumption of bivariate normality of $\varepsilon_t|\psi_{t-1}$, as stated in the preceding section, the log-likelihood function (up to a constant) is given by

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}\left(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t\right) \tag{4.7}$$

where H_t is as given in equation (4.6) and θ is the vector of all parameters involved in this model. Obtaining the ML estimates of this model requires optimization of a highly nonlinear objective function (conditional on some starting values for H_0 and other relevant parameters). To that end, we have used the standard gradient search algorithm called the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

Further, all programs required for obtaining the estimates as well as for carrying out testing of hypothesis have been written in GAUSS.

4.3.2 Testing of hypothesis

We test for spillovers in means, variances, and 'BTGARCH-in-mean' effects for the proposed model in equation (4.6) by placing appropriate restrictions on the relevant parameters and carrying out the Wald test. The Wald test statistic, in terms of general linear restrictions i.e., under the null hypothesis $R\theta = \xi$, is given as:

$$W = [R\hat{\theta} - \xi]'[R\hat{V}(\hat{\theta})R']^{-1}[R\hat{\theta} - \xi] \tag{4.8}$$

where R is a $q \times k$ matrix of known constants with $q < k$, q is a number of restrictions, k is the number of parameters i.e, number of elements in θ, ξ is a $q \times 1$ vector of known constants, $\hat{\theta}$ is the $k \times 1$ vector of the estimated parameters under the unrestricted model, and $\hat{V}(\hat{\theta})$ is the estimated variance-covariance matrix of the estimated parameters. $W \sim \chi^2_q$ asymptotically, under the null hypothesis.

Now we state the different null hypotheses which specify the absence of each of the 3 different kinds of spillovers or transmissions for each of the two market movements as well as equality of spillovers in the two market movements.

1. *Tests of spillovers in conditional mean*

   (a) H^a_{01}: No spillovers in mean from second stock market to first stock market in both up and down market movements i.e., $b^1_{12} = b^2_{12} = 0$.

   (b) H^b_{01}: No spillovers in mean from first stock market to second stock market in both up and down market movements i.e., $b^1_{21} = b^2_{21} = 0$.

2. *Tests of equality of spillovers in the two stock market movements - up and down*

   (a) H^a_{02}: Equal spillovers in mean in up and down market conditions, from second market to first market i.e., $b^1_{12} = b^2_{12}$.

   (b) H^b_{02}: Equal spillovers in mean in up and down market conditions, from first market to second market i.e., $b^1_{21} = b^2_{21}$.

3. *Test of spillovers in the asymmetric component (due to leverage effect) of variance from second market to first market as well as from first to second*

No spillovers in the asymmetric component from both directions i.e., H_{03}: $d_{12} = d_{21} = 0$.

4. *Test of spillovers in the symmetric component of variance from one market to another*

   (a) No spillovers from second market to first market i.e., H_{04}^{a}: $\alpha_{12} = \beta_{12} = 0$.

   (b) No spillovers from firsts market to second market i.e., H_{04}^{b}: $\alpha_{21} = \beta_{21} = 0$.

5. *Test of spillovers in the symmetric component of variance from second market to first market as well as from first to second*

   No spillovers in the symmetric component from both directions i.e., H_{05}: $\alpha_{12} = \alpha_{21} = \beta_{12} = \beta_{21} = 0$.

6. *Tests of no BTGARCH-in-mean effect from one market to another*

   (a) No spillovers of direct risk of second stock market to the mean of first stock market in both up and down market movements i.e., H_{06}^{a}: $\lambda_{13}^{1} = \lambda_{13}^{2} = 0$.

   (b) No spillovers of direct risk of first stock market to the mean of second stock market in both up and down market movements i.e., H_{06}^{b}: $\lambda_{21}^{1} = \lambda_{21}^{2} = 0$.

   (c) No spillovers of indirect (through covariance term , h_{12t}) risk on the conditional mean of the first market in both up and down market movements i.e., H_{06}^{c}: $\lambda_{12}^{1} = \lambda_{12}^{2} = 0$.

   (d) No spillovers of indirect (through covariance term , h_{12t}) risk on the conditional mean of the second market in both up and down market movements i.e., H_{06}^{d}: $\lambda_{22}^{1} = \lambda_{22}^{2} = 0$.

7. *Test of equality of each of the parameters of BTGARCH-in-mean effects in up and down market movements*

   H_{07}: $\lambda_{11}^{1} = \lambda_{11}^{2}$; $\lambda_{12}^{1} = \lambda_{12}^{2}$; $\lambda_{13}^{1} = \lambda_{13}^{2}$; $\lambda_{21}^{1} = \lambda_{21}^{2}$; $\lambda_{22}^{1} = \lambda_{22}^{2}$; $\lambda_{23}^{1} = \lambda_{23}^{2}$.

Finally, noting that all the four other models i.e., the VAR-BGARCH, VAR-BGARCH-M, VAR-BTGARCH-M and TVAR-BGARCH-M, are nested to the proposed model i.e., the TVAR-BTGARCH-M, we have carried out the likelihood ratio (LR) test to conclude if one or more of the modelling considerations which are incorporated in the proposed model have indeed led to statistically significant improvements. The LR test statistic is given by

$$LR = -2(L(\theta_0) - L(\theta_1)) \tag{4.9}$$

where $L(\theta_0)$ stands for the maximized value of the log-likelihood function under restrictions and $L(\theta_1)$ is the maximized log-likelihood value without restrictions. This test statistic follows, asymptotically, a χ^2 distribution with q degrees of freedom under the null hypothesis where q is the number of independent restrictions.

4.4 Empirical Results

In this section we discuss first the results of estimation of all the models considered in this chapter. Thereafter we report the findings on the tests of hypotheses mentioned in the preceding section. The data, as already mentioned in Chapter 2, consist of stock indices at daily frequency for eight countries - four from developed countries (*viz.*, the USA, the UK, Hong Kong and Japan) and four from important emerging economies (*viz.*, Brazil, Russia, India, and China, called the BRIC group) covering the period from 1^{st} January 2000 to 31^{st} December 2012. The details of the data set and the preliminary statistics of each returns series have already been discussed in Chapter 2. It may be recalled that all the return series were found to be stationary and that none of the series was found to have any structural break. Since this study involves several countries and the models considered in this chapter take bivariate returns data together, we have to avoid the problem of different holidays for different stock markets, and make the data sets uniform. Following the usual practice, we take care of this problem by taking the common dates at which all the markets were open and delete the data on those dates when at least one stock market was closed. The computations are done separately for 28 pairs[4] of stock returns. It may be noted that from consideration of the two groups of countries considered in this work, we have essentially three types of combinations of countries *viz.*, developed-developed (D-D), emerging-emerging (E-E) and developed-emerging (D-E).

4.4.1 Estimated models

In this study, we have considered, in all, five models and obtained the ML estimates of the parameters involved by following the algorithm mentioned in Section 4.3.1. Besides the proposed model - TVAR-MTGARCH-M - as well as the one with symmetric BEKK specification i.e., TVAR-BGARCH-M, the other three models considered are VAR-BGARCH, VAR-BGARCH-M and VAR-BTGARCH-M. The first model of the latter group refers to simple multivariate GARCH model which does not allow the

[4]With 2 countries at a time from the group of 8 countries, we have a total of 28 pairs of countries.

conditional variance to directly affect the conditional mean. The other two models are multivariate GARCH-in-mean models where the conditional mean model has no consideration to stock market movements characterized as up and down markets, and the conditional variance model is taken to be bivariate GARCH and bivariate TGARCH models, respectively. These models are obviously special cases of the proposed model.

4.4.1.1 *VAR-BGARCH model*

We first report the estimates of the VAR-BGARCH model[5] for all the 28 pairs of countries in Table 4.1. In this model, the mean is specified as VAR(1) and the conditional variance has the symmetric BEKK representation (*cf.* equation (4.2) for the bivariate case). It may be noted that this is the simplest model since it considers neither the two different market conditions nor the asymmetry in the conditional variance for the purpose of modelling. It also does not consider the GARCH-in-mean effect. It is noted that the coefficients attached to the first lag of the two return series in the two equations are significant in many of the 28 bivariate models estimated. More explicitly, this holds more often for the combinations of countries where both are developed than those belonging to emerging-emerging (E-E) combination. Likewise, insofar as the bivariate (symmetric) GARCH model is concerned, we find that the parameters are mostly significant.

Now, we look at the parameters capturing different spillovers. As regards mean spillover from one market to another in the developed-developed (D-D) combination, we first note all the spillovers are found to be positive. Further, we find that b_{21} is significant in all 6 combinations; and b_{12} is significant in 3 combinations only *viz.*, from UK to US, from Hong Kong to US, and from Japan to US. In other words, b_{12} is insignificant in the remaining 3 combinations *viz.*, from Hong Kong to UK, Japan to UK and Japan to Hong Kong. In the E-E combination it is significant to note that Brazil and India have significant positive mean spillover effect in both directions. While those between India and China are both insignificant. Out of the remaining four pairs *viz.*, from Brazil to Russia, from Brazil to China , from Russia to India, and Russia to China, the spillovers are positive and significant while in all these 4 combinations the effects in reverse directions are insignificant. Thus it may be concluded that between these two groups of countries, the mean spillovers are more often significant in D-D combination than in

[5]As already mentioned in Section 4.2, only the first lag value of returns has been taken for all the models and that this choice has been found to be adequate in most cases by the Ljung-Box $Q(\cdot)$ test with standardized residuals. Similarly, the orders of GARCH/TGARCH model have been taken to be (1,1) for all the models and this choice has also been found to be adequate by the $Q(\cdot)$ test with squared standardized residuals.

E-E combination, as expected. Finally, amongst the 16 pairs in developed-emerging (D-E) combination, the mean spillover is significant in 13 cases in at least one direction. The number of combinations where there are no effects is 3, and these are US-Brazil, UK-Russia and Hong Kong - China.

It may be stated that while it is expected that there would be spillover effects between the US and Brazil, but the results show otherwise. This may be due to the fact that these results correspond to the VAR-BGARCH model where, neither in mean nor in volatility, asymmetric reactions are considered. Further, volatility-in-mean effect is also not included in this model. When the appropriate model for the data generating process is specified, as in our proposed model, it is expected that the spillover effects between the US and Brazil would be found. It is further noted that the number of pairs with significant spillovers in each of the two directions *viz.*, from developed to emerging and from emerging to developed is same and the number is nine. This means the incidence of such mean spillovers is significant for a little more than half of the combinations. It may be also be noted that there are, in all, 5 pairs *viz.*, UK - India, Hong Kong-Brazil, Hong Kong-India , Japan-Brazil, and Japan-India where the spillovers are in both directions.

It is noteworthy that in all cases of significant mean spillovers, the coefficient values are positive except for the spillover effects from China to Japan, which is negative. This means that except for the last case, the two underlying stock markets move in the same direction for all pairs in all the 3 combinations of markets considered in this study. The finding that the mean spillover effect from China to Japan is significant and negative is rather striking, especially because the effect in the other direction *viz.*, from Japan to China, has been found to be insignificant.

Now insofar as the volatility spillovers between any two markets is concerned, we find that in the 6 pairs of markets under D-D combination, except for UK-Hong Kong pair, all others have significant effects. This is so because one or more of the parameters, α_{12}, α_{21}, β_{12}, β_{21}, are found to be significant. In the E-E combination, all pairs are found to have significant volatility spillovers. And finally, in the 16 pairs of markets under D-E combination, we find that there are 5 pairs *viz.*, US-Brazil, US-Russia, US-India, US-China, and UK-China, where there are no cross-volatility dependences, and in the remaining 11 these dependences are significant. It is further noted that the only pair of markets where there is no spillovers both in mean and variance is US-Brazil. On the whole, therefore, we conclude by saying that, based on the simple model in the bivariate set-up which is also being considered as a benchmark model for this study, the incidence of mean spillovers as well as variance spillovers which is also called the cross-volatility dependence is quite significant. Further, the few cases where one or more of these spillovers are not statistically significant are mostly in the D-E combination of stock markets.

Table 4.1: Estimates of the parameters of VAR-BGARCH model

A: Parameters in the VAR part of conditional mean						
	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}
Developed-Developed (D-D) combination						
US-UK	0.0526	0.0433	-0.0916	0.3371	0.0342	-0.2467
	(0.01)	(0.01)	(0.00)	(0.00)	(0.04)	(0.00)
US-HO	0.0478	0.0664	-0.0818	0.4745	0.023	-0.1035
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)
US-JAP	0.052	0.0029	-0.0892	0.5027	0.0217	-0.0761
	(0.00)	(0.89)	(0.00)	(0.00)	(0.10)	(0.00)
UK-HO	0.0527	0.0585	-0.0627	0.3458	0.0153	-0.1182
	(0.00)	(0.00)	(0.00)	(0.00)	(0.21)	(0.00)
UK-JAP	0.0535	0.0186	-0.0507	0.3821	0.0189	-0.1039
	(0.00)	(0.47)	(0.01)	(0.00)	(0.16)	(0.00)
HO-JAP	0.0868	0.0364	0.0157	0.0796	-0.0242	-0.0351
	(0.00)	(0.07)	(0.50)	(0.00)	(0.24)	(0.14)
Emerging-Emerging (E-E) combination						
BR-RUS	0.108	0.1568	-0.0392	0.1872	0.0216	-0.0566
	(0.00)	(0.00)	(0.06)	(0.00)	(0.17)	(0.00)
BR-IND	0.1192	0.1409	-0.0487	0.1213	0.0412	0.0087
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.65)
BR-CH	0.1017	0.0069	-0.0169	0.0755	0.0091	-0.0217
	(0.00)	(0.80)	(0.19)	(0.00)	(0.63)	(0.25)
RUS-IND	0.1583	0.1567	-0.002	0.0658	0.0193	0.0086
	(0.00)	(0.00)	(0.90)	(0.00)	(0.14)	(0.62)
RUS-CH	0.1542	0.0078	0.0086	0.0459	-0.0207	-0.0186
	(0.00)	(0.73)	(0.54)	(0.00)	(0.15)	(0.16)
IND-CH	0.1615	0.0146	0.0584	0.013	-0.0084	-0.0149
	(0.00)	(0.48)	(0.00)	(0.35)	(0.52)	(0.26)
Developed-Emerging (D-E) combination						
US-BR	0.0429	0.0832	-0.0776	0.0424	0.0018	-0.0232
	(0.00)	(0.00)	(0.00)	(0.24)	(0.89)	(0.33)
US-RUS	0.0501	0.1245	-0.0819	0.2937	-0.0024	-0.0467
	(0.00)	(0.00)	(0.00)	(0.00)	(0.82)	(0.01)
US-IND	0.0543	0.13	-0.0892	0.2635	0.0012	-0.0018
	(0.00)	(0.00)	(0.00)	(0.00)	(0.91)	(0.92)
US-CH	0.0411	0.0084	-0.0763	0.1411	0.0077	-0.0112
	(0.00)	(0.76)	(0.00)	(0.00)	(0.52)	(0.52)
UK-BR	0.0435	0.0841	-0.1238	0.0466	0.0888	-0.0518
	(0.01)	(0.01)	(0.00)	(0.14)	(0.00)	(0.01)
UK-RUS	0.0562	0.133	-0.0514	0.0111	0.0132	0.0087
	(0.00)	(0.00)	(0.01)	(0.70)	(0.18)	(0.67)

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Table: 4.1 Continued from previous page

	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}
UK-IND	0.0481	0.1351	-0.062	0.155	0.0317	0.0165
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.44)
UK-CH	0.0529	0.0097	-0.0492	0.11	0.0041	-0.0178
	(0.00)	(0.67)	(0.00)	(0.00)	(0.70)	(0.21)
HO-BR	0.0518	0.1018	-0.0753	0.062	0.2264	-0.0573
	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HO-RUS	0.0684	0.161	-0.0598	0.0362	0.0964	-0.0163
	(0.01)	(0.00)	(0.00)	(0.18)	(0.00)	(0.45)
HO-IND	0.1043	0.1415	-0.0367	0.0427	0.0639	0.0309
	(0.00)	(0.00)	(0.08)	(0.03)	(0.00)	(0.06)
HO-CH	0.0665	0.0151	0.0117	0.0202	-0.0156	0.0037
	(0.00)	(0.23)	(0.43)	(0.14)	(0.18)	(0.79)
JAP-BR	0.024	0.0945	-0.059	0.0382	0.2304	-0.031
	(0.26)	(0.00)	(0.00)	(0.02)	(0.00)	(0.09)
JAP-RUS	0.0464	0.178	-0.0551	0.0104	0.1339	0.0031
	(0.03)	(0.00)	(0.00)	(0.67)	(0.00)	(0.88)
JAP-IND	0.0316	0.1629	-0.0318	0.0266	0.0849	0.0265
	(0.17)	(0.00)	(0.05)	(0.07)	(0.00)	(0.14)
JAP-CH	0.0562	0.027	0.0107	0.0049	-0.035	-0.0003
	(0.01)	(0.33)	(0.51)	(0.70)	(0.00)	(0.98)

B: Parameters in the BTGARCH part

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Developed-Developed (D-D) combination											
US-UK	-0.1387	-0.1014	0.1143	0.2059	0.0947	-0.0597	0.3426	0.9752	-0.029	0.0174	0.9339
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.11)	(0.00)	(0.00)	(0.01)	(0.09)	(0.00)
US-HO	-0.1381	-0.1153	0.1426	0.2049	0.093	-0.0844	0.2919	0.9722	-0.031	0.025	0.9479
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	-0.1158	-0.0492	0.3047	0.2587	-0.0526	0.0227	0.2845	0.9627	0.009	0.0077	0.9343
	(0.00)	(0.40)	(0.00)	(0.00)	(0.01)	(0.44)	(0.00)	(0.00)	(0.24)	(0.44)	(0.00)
UK-HO	-0.1651	-0.0566	0.1372	0.3512	-0.0301	0.0412	0.208	0.9333	0.0044	-0.0033	0.9719
	(0.00)	(0.03)	(0.00)	(0.00)	(0.19)	(0.13)	(0.00)	(0.00)	(0.49)	(0.73)	(0.00)
UK-JAP	-0.1597	-0.1179	0.2693	0.3271	-0.0272	-0.0466	0.2734	0.948	-0.0096	0.0421	0.9339
	(0.00)	(0.01)	(0.00)	(0.00)	(0.10)	(0.20)	(0.00)	(0.00)	(0.24)	(0.01)	(0.00)
HO-JAP	-0.1518	-0.2282	0.2009	0.2243	0.0273	0.017	0.2829	0.9813	-0.0243	0.0137	0.9301
	(0.00)	(0.00)	(0.00)	(0.00)	(0.28)	(0.53)	(0.00)	(0.00)	(0.01)	(0.08)	(0.00)
Emerging-Emerging (E-E) combination											
BR-RUS	-0.341	-0.3518	0.0793	0.2251	0.009	0.0621	0.2979	0.9603	-0.0028	-0.0326	0.9472
	(0.00)	(0.00)	(0.53)	(0.00)	(0.65)	(0.04)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)
BR-IND	-0.2945	-0.2242	0.4062	0.2274	-0.0117	0.046	0.3375	0.9655	-0.0064	-0.0033	0.9029
	(0.00)	(0.00)	(0.00)	(0.00)	(0.63)	(0.05)	(0.00)	(0.00)	(0.56)	(0.72)	(0.00)
BR-CH	-0.3612	0.0169	0.1762	0.25	-0.0672	-0.0161	0.216	0.9498	0.0192	0.005	0.9714
	(0.00)	(0.24)	(0.00)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.15)	(0.00)
RUS-IND	-0.3075	-0.2629	0.3117	0.2833	0.0582	-0.0454	0.3392	0.9632	-0.0667	0.0333	0.9073

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Table: 4.1 Continued from previous page

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RUS-CH	-0.3413	0.0072	0.1581	0.3339	-0.0781	-0.0079	0.1915	0.9336	0.0165	0.0049	0.9769
	(0.00)	(0.81)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.00)	(0.11)	(0.00)
IND-CH	-0.4525	-0.0027	0.1679	0.3633	-0.0475	-0.0267	0.2133	0.9002	0.0211	0.0075	0.9721
	(0.00)	(0.93)	(0.00)	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.24)	(0.00)
Developed-Emerging (D-E) combination											
US-BR	0.1435	0.2296	0.1085	0.2688	0.0037	0.034	0.2052	0.96	-0.0028	-0.0113	0.9725
	(0.00)	(0.00)	(0.00)	(0.00)	(0.78)	(0.29)	(0.00)	(0.00)	(0.47)	(0.17)	(0.00)
US-RUS	-0.1363	-0.1044	0.2723	0.2517	-0.0086	-0.0052	0.3014	0.9629	0.0023	0.0027	0.9475
	(0.00)	(0.03)	(0.00)	(0.00)	(0.35)	(0.87)	(0.00)	(0.00)	(0.45)	(0.79)	(0.00)
US-IND	0.1503	0.2401	0.3401	0.2633	-0.0015	0.0462	0.2995	0.9615	-0.0072	-0.0078	0.9249
	(0.00)	(0.00)	(0.00)	(0.00)	(0.90)	(0.11)	(0.00)	(0.00)	(0.20)	(0.44)	(0.00)
US-CH	0.1549	0.0168	0.1675	0.2687	-0.0047	-0.0121	0.1991	0.9566	0.0016	0.002	0.9757
	(0.00)	(0.62)	(0.00)	(0.00)	(0.68)	(0.41)	(0.00)	(0.00)	(0.65)	(0.66)	(0.00)
UK-BR	0.1561	0.1884	0.1666	0.3362	-0.0183	0.1416	0.1732	0.9403	0.0004	-0.0372	0.9771
	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.00)	(0.00)	(0.00)	(0.92)	(0.00)	(0.00)
UK-RUS	0.1531	0.1957	0.1781	0.3012	0.0114	0.0519	0.2852	0.9475	-0.003	-0.0251	0.9564
	(0.00)	(0.00)	(0.00)	(0.00)	(0.17)	(0.09)	(0.00)	(0.00)	(0.20)	(0.01)	(0.00)
UK-IND	0.1517	0.2127	0.4423	0.2961	-0.0024	-0.0714	0.374	0.9536	-0.0075	0.0425	0.886
	(0.00)	(0.00)	(0.00)	(0.00)	(0.86)	(0.17)	(0.00)	(0.00)	(0.32)	(0.04)	(0.00)
UK-CH	-0.1573	0.0245	0.1582	0.3266	-0.0079	0.0073	0.189	0.9389	0.0046	-0.0013	0.978
	(0.00)	(0.46)	(0.00)	(0.00)	(0.45)	(0.65)	(0.00)	(0.00)	(0.16)	(0.83)	(0.00)
HO-BR	0.1616	0.2282	0.2224	0.2247	0.0304	-0.0165	0.2282	0.9714	-0.012	0.0039	0.9609
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.55)	(0.00)	(0.00)	(0.01)	(0.59)	(0.00)
HO-RUS	0.1514	0.2122	0.262	0.2267	0.0232	0.0113	0.3143	0.9713	-0.0068	-0.005	0.9416
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.80)	(0.00)	(0.00)	(0.09)	(0.70)	(0.00)
HO-IND	0.229	0.2638	0.1978	0.3315	-0.0281	0.2191	0.2047	0.94	0.0037	-0.0606	0.95
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)
HO-CH	0.1524	0.0006	0.1691	0.2664	-0.0425	-0.0252	0.2134	0.9596	0.0111	0.0079	0.9715
	(0.00)	(0.99)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
JAP-BR	0.2661	0.0872	0.2363	0.3032	-0.0061	0.0687	0.1823	0.9391	0.0048	-0.0268	0.9767
	(0.00)	(0.14)	(0.00)	(0.00)	(0.75)	(0.01)	(0.00)	(0.00)	(0.55)	(0.00)	(0.00)
JAP-RUS	0.2585	0.1487	0.3289	0.2612	0.0386	0.0088	0.3205	0.9542	-0.0156	0.003	0.9367
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.71)	(0.00)	(0.00)	(0.00)	(0.80)	(0.00)
JAP-IND	-0.1795	0.2866	0.0846	0.2196	0.1051	-0.1514	0.3435	0.9783	-0.0569	0.11	0.8952
	(0.00)	(0.04)	(0.86)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JAP-CH	-0.3098	0.0151	0.1769	0.311	-0.0147	0.004	0.209	0.9324	0.0078	0.0017	0.9728
	(0.00)	(0.62)	(0.00)	(0.00)	(0.28)	(0.79)	(0.00)	(0.00)	(0.10)	(0.77)	(0.00)

Note: $p-$values are given in parenthesis

4.4.1.2 *VAR-BGARCH-M*

In this model, we incorporate explicitly the conditional variance in the conditional mean specification to capture the relationship between return and volatility. As the framework is bivariate GARCH-in-mean, this model directly introduces, in the conditional mean model, not only the effects of changing conditional variances of returns on both the stock markets but also the effects of changing cross-volatilities as measured by the conditional covariances. The estimates of the parameters of this model for all the 28 pairs of markets are given in Table 4.2. For this model, we primarily discuss about the BGARCH-in-meam spillover effects since this is the new feature, as compared to VAR-BGARCH model. Insofar as the mean spillovers are concerned, the findings are, by and large, the same as in the benchmark model. It is only that instead of 3 pairs of countries in the D-E combination, we now have only 2 (the pairs are the same *viz.*, UK-Russia and Hong Kong-China) where there is no spillovers in mean in either direction; the US-Brazil pair of markets has spillover effects from US to Brazil. As regards the effects in both directions, we now have 4 pairs in the D-E combination and 1 pair each in the D-D and E-E combinations instead of 5, 3 and 1 respectively, in the benchmark model.

With regard to spillovers in variances and covariances we note that, as expectedly, the findings are almost the same as in case of VAR-BGARCH model. For the D-D combination of countries, the cross volatility dependences are found for the same five pairs of countries as in the VAR-BGARCH model. It is the UK-Hong Kong pair where no cross volatility dependences are found. While all pairs in E-E combination have spillovers, the findings for the D-E combination is that unlike in VAR-BGARCH model, we now have 3 pairs of countries where there are no volatility spillovers. These countries are the same as in VAR-BGARCH model *viz.*, US-Russia, US-China and UK-China. The other two countries *viz.*, UK-Brazil, and US-India, where no cross volatility dependence was found for the benchmark VAR-BGARCH model, are found to have significant spillovers in variances and covariances in case of the VAR-BGARCH-M model.

We now come to the main feature of this model compared to the VAR-BGARCH model *viz.*, the direct incorporation of time varying risk, as specified by H_t, in the conditional mean. The direct BGARCH-in-mean effect as captured by λ_{13} and λ_{21} are found to be significant in 5 pairs in D-D combination, in 3 pairs in E-E combination, and 8 pairs in D-E combination. Thus, the incidence of this spillover of risk of one country affecting the mean of the other country in the pair is least in case of E-E combination. This finding is somewhat likely since the mutual flow of capital investments among emerging countries is not likely to be significant among themselves. The pairs in which the risk spillovers in E-E combination are found are from Russia to India, Russia to China, and India to Brazil. In the D-E combination, the spillovers are mostly from developed to emerging markets, and US-Russia and Japan-Brazil have the spillovers in both ways. This finding is also in the expected line since it is more often the case that the risk of developed economy would have an impact on the returns on the emerging economy, and not the *vice versa* that often. While this spillover is present in the pairs under D-D combination in at least one direction in 5 pairs (out of 6 pairs) in one direction, the reverse is true only for 1 pair i.e., from UK to US. Finally UK-Hong Kong pair has both the coefficients insignificant, which means the risk of one market does not affect the risk of the other.

As regards the similar spillover effects through covariance term of H_t i.e., in terms of the parameters λ_{12} , λ_{22}, the number of significant cases are 3, 3 and 7 for D-D , E-E and D-E combinations, respectively. Thus, incidence of this indirect (covariance) transmission channel is somewhat reduced for D-D and and D-E combinations as compared to the same for direct (variance) transmission channel, as mentioned in the preceding paragraph. Finally, we note that the estimates of all the four $\lambda-$parameters (i.e., λ_{13}, λ_{21}, λ_{12}, λ_{22}) stated above have been found to be negative except for 5 cases *viz.* from Japan to Russia, from Japan to China in case of direct transmission, and in Japan-Brazil, Japan-Hong Kong, US-UK in case of indirect transmission channel. The possible explanation for obtaining negative estimates could be the prevalence of volatility feedback (as in the univariate case) type of phenomenon in the behaviour of the two markets concerned. However, when we look at the coefficients λ_{11} and λ_{23}, we find that barring Hong Kong-Japan pair for λ_{11}, both the coefficient are positive in all the 3 combinations where the estimates are significant. To be more specific, the numbers of such cases are 3, 1, 5 for λ_{11} and 2, 2, 6 in λ_{23}, in D-D, E-E, and D-E combinations, respectively, in both cases. Thus, these findings suggest that in terms of own risk-return behaviour in the BGARCH-in-mean component, high risk is found to be associated with high expected return.

Table 4.2: Estimates of the parameters of VAR-BGARCH-M model

A: Parameters in the conditional mean part												
	Parameters in the VAR component						**Parameters in the BTGARCH-in-mean component**					
	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}	λ_{11}	λ_{12}	λ_{13}	λ_{21}	λ_{22}	λ_{23}
Developed-Developed (D-D) combination												
US-UK	0.0342	0.0463	-0.0961	0.3219	0.0459	-0.2422	0.154	-0.1031	0.0866	0.3402	-0.2128	-0.0992
	(0.23)	(0.08)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.04)	(0.49)	(0.00)	(0.00)	(0.12)
US-HO	0.0413	0.0642	-0.0822	0.4738	0.0225	-0.1050	0.0329	-0.0312	-0.0163	0.0119	-0.0118	0.0250
	(0.11)	(0.04)	(0.00)	(0.00)	(0.11)	(0.00)	(0.07)	(0.07)	(0.71)	(0.81)	(0.49)	(0.31)
US-JAP	0.0359	0.0199	-0.0888	0.5028	0.0223	-0.0804	0.0320	-0.0589	-0.0487	-0.0025	-0.0001	0.0416
	(0.27)	(0.59)	(0.00)	(0.00)	(0.11)	(0.00)	(0.21)	(0.02)	(0.35)	(0.97)	(0.99)	(0.06)
UK-HO	0.0454	0.0670	-0.0643	0.3452	0.0131	-0.1221	0.0695	-0.0162	-0.0828	-0.0279	-0.0040	0.0205
	(0.12)	(0.08)	(0.00)	(0.00)	(0.33)	(0.00)	(0.03)	(0.54)	(0.19)	(0.69)	(0.82)	(0.43)
UK-JAP	0.0298	-0.0194	-0.0492	0.3870	0.0180	-0.1138	0.0216	-0.0698	-0.0573	-0.0908	0.0186	0.0974
	(0.21)	(0.69)	(0.01)	(0.00)	(0.18)	(0.00)	(0.30)	(0.01)	(0.13)	(0.10)	(0.23)	(0.00)
HO-JAP	0.1416	0.1052	0.0156	0.0804	-0.0255	-0.0380	-0.0866	-0.0873	0.1635	0.1203	-0.0341	-0.0079
	(0.01)	(0.07)	(0.48)	(0.00)	(0.20)	(0.09)	(0.06)	(0.03)	(0.06)	(0.16)	(0.30)	(0.84)
Emerging-Emerging (E-E) combination												

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Table: 4.2 Continued from previous page

	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}	λ_{11}	λ_{12}	λ_{13}	λ_{21}	λ_{22}	λ_{23}
BR-RUS	0.0270	0.2132	-0.0390	0.1869	0.0202	-0.0575	0.0339	-0.0116	0.0107	-0.0259	-0.0120	0.0070
	(0.68)	(0.01)	(0.04)	(0.00)	(0.20)	(0.00)	(0.17)	(0.63)	(0.74)	(0.53)	(0.29)	(0.67)
BR-IND	0.0892	0.2263	-0.0500	0.1201	0.0390	0.0054	0.0275	-0.0273	0.0212	0.0015	-0.0275	0.0092
	(0.23)	(0.00)	(0.01)	(0.00)	(0.05)	(0.79)	(0.22)	(0.13)	(0.61)	(0.97)	(0.08)	(0.66)
BR-CH	0.0198	-0.0675	-0.0167	0.0768	0.0082	-0.0246	0.0208	0.0034	0.0027	-0.0702	0.0015	0.0382
	(0.81)	(0.30)	(0.31)	(0.00)	(0.48)	(0.09)	(0.32)	(0.81)	(0.96)	(0.13)	(0.93)	(0.05)
RUS-IND	0.2057	0.1569	0.0031	0.0695	0.0091	-0.0156	0.0247	-0.0090	-0.0678	0.0006	-0.0147	0.0089
	(0.00)	(0.00)	(0.88)	(0.00)	(0.69)	(0.41)	(0.08)	(0.34)	(0.09)	(0.98)	(0.51)	(0.65)
RUS-CH	0.2248	-0.0686	0.0059	0.0467	-0.0228	-0.0193	0.0041	0.0019	-0.1076	-0.0083	-0.0110	0.0264
	(0.00)	(0.18)	(0.75)	(0.00)	(0.20)	(0.29)	(0.68)	(0.71)	(0.02)	(0.76)	(0.53)	(0.17)
IND-CH	0.2062	-0.0791	0.0563	0.0160	-0.0081	-0.0162	-0.0046	0.0072	0.0230	-0.1040	-0.0168	0.0503
	(0.00)	(0.17)	(0.01)	(0.31)	(0.62)	(0.41)	(0.80)	(0.52)	(0.66)	(0.04)	(0.31)	(0.02)
Developed-Emerging (D-E) combination												
US-BR	0.0722	0.0068	-0.0791	0.0439	0.0019	-0.0245	0.0157	0.0134	0.0437	0.0027	-0.0288	0.0192
	(0.10)	(0.92)	(0.00)	(0.05)	(0.87)	(0.18)	(0.62)	(0.79)	(0.30)	(0.97)	(0.11)	(0.54)
US-RUS	0.0603	0.1858	-0.0848	0.2925	-0.0039	-0.0486	0.0493	-0.0634	-0.016	0.0288	-0.0106	0.0064
	(0.01)	(0.00)	(0.00)	(0.00)	(0.71)	(0.01)	(0.05)	(0.05)	(0.63)	(0.58)	(0.01)	(0.58)
US-IND	0.0493	0.1608	-0.0897	0.263	0.001	-0.0042	0.0185	-0.0273	0.0013	0.0076	-0.0048	0.0054
	(0.14)	(0.00)	(0.00)	(0.00)	(0.93)	(0.83)	(0.37)	(0.16)	(0.96)	(0.87)	(0.61)	(0.78)
US-CH	0.0797	-0.0551	-0.0775	0.1422	0.0091	-0.0129	0.0292	-0.0092	0.013	-0.0193	-0.0248	0.0355
	(0.00)	(0.19)	(0.00)	(0.00)	(0.39)	(0.38)	(0.06)	(0.51)	(0.73)	(0.79)	(0.00)	(0.02)
UK-BR	0.1123	0.0541	-0.1249	0.0458	0.0874	-0.0538	0.0579	-0.0236	0.0055	-0.0058	-0.037	0.026
	(0.01)	(0.45)	(0.00)	(0.13)	(0.00)	(0.01)	(0.12)	(0.64)	(0.90)	(0.93)	(0.02)	(0.35)
UK-RUS	0.0774	0.1853	-0.053	0.0106	0.0123	0.0055	0.0343	-0.023	-0.0046	-0.0273	-0.0091	0.0099
	(0.00)	(0.00)	(0.00)	(0.73)	(0.19)	(0.78)	(0.03)	(0.46)	(0.82)	(0.56)	(0.12)	(0.45)
UK-IND	0.0555	0.1757	-0.0643	0.1472	0.0305	0.0102	0.025	-0.0544	-0.0146	0.0384	-0.0059	0.0093
	(0.05)	(0.00)	(0.00)	(0.00)	(0.01)	(0.55)	(0.30)	(0.01)	(0.72)	(0.41)	(0.43)	(0.61)
UK-CH	0.081	-0.0635	-0.0509	0.1105	0.0048	-0.0194	0.031	-0.0094	-0.0299	-0.0445	-0.0181	0.0411
	(0.02)	(0.20)	(0.00)	(0.00)	(0.66)	(0.22)	(0.03)	(0.53)	(0.31)	(0.46)	(0.06)	(0.02)
HO-BR	0.1014	-0.0427	-0.0748	0.0619	0.2254	-0.0575	0.0038	0.0213	0.0164	-0.0859	-0.02	0.0515
	(0.11)	(0.62)	(0.00)	(0.01)	(0.00)	(0.00)	(0.87)	(0.34)	(0.70)	(0.09)	(0.34)	(0.09)
HO-RUS	0.0592	0.166	-0.0634	0.0329	0.0959	-0.0173	0.0254	0.0057	-0.026	-0.0861	-0.0017	0.0214
	(0.10)	(0.00)	(0.00)	(0.19)	(0.00)	(0.33)	(0.12)	(0.75)	(0.30)	(0.00)	(0.82)	(0.08)
HO-IND	0.0503	0.1975	-0.0269	0.0743	0.0594	-0.0050	0.0013	-0.1195	0.0101	0.1494	0.0070	0.0050
	(0.19)	(0.00)	(0.20)	(0.00)	(0.00)	(0.83)	(0.96)	(0.00)	(0.83)	(0.01)	(0.65)	(0.82)
HO-CH	0.0434	-0.0840	0.0115	0.0219	-0.0156	0.0014	0.0165	0.0195	0.0010	-0.0767	-0.0044	0.0474
	(0.31)	(0.10)	(0.55)	(0.18)	(0.33)	(0.93)	(0.37)	(0.15)	(0.98)	(0.07)	(0.77)	(0.03)
JAP-BR	0.2383	0.0873	-0.0653	0.0355	0.2314	-0.0289	0.0307	-0.0022	0.0892	0.0361	-0.0888	-0.0005
	(0.00)	(0.35)	(0.00)	(0.10)	(0.00)	(0.11)	(0.20)	(0.93)	(0.07)	(0.53)	(0.00)	(0.99)
JAP-RUS	0.0564	0.1285	-0.0589	0.0098	0.1317	0.0022	0.0326	0.0400	-0.0375	-0.0877	-0.0085	0.0093
	(0.16)	(0.05)	(0.00)	(0.59)	(0.00)	(0.91)	(0.10)	(0.10)	(0.14)	(0.09)	(0.26)	(0.49)
JAP-IND	0.0277	0.1748	-0.0315	0.0267	0.0847	0.0265	0.0047	-0.0073	-0.0280	0.0155	0.0072	-0.0042
	(0.53)	(0.00)	(0.06)	(0.13)	(0.00)	(0.12)	(0.87)	(0.72)	(0.52)	(0.73)	(0.66)	(0.85)
JAP-CH	0.1046	-0.1345	0.0093	0.0066	-0.0357	-0.0057	0.0059	0.0327	-0.0336	-0.1747	-0.0150	0.0627
	(0.09)	(0.03)	(0.54)	(0.60)	(0.01)	(0.68)	(0.80)	(0.06)	(0.54)	(0.00)	(0.27)	(0.00)

B: Parameters in the BTGARCH part

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Developed-Developed (D-D) combination											
US-UK	0.0388	-0.1615	0.0016	0.0772	0.2874	-0.2127	0.3544	1.1619	-0.4369	0.392	0.6172
	(0.54)	(0.00)	(1.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-HO	0.1393	0.1130	0.1421	0.2072	0.0933	-0.0843	0.2894	0.9715	-0.0309	0.0254	0.9485
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	0.1237	0.0525	0.3002	0.2647	-0.0512	0.0184	0.2866	0.9613	0.0070	0.0102	0.9341
	(0.00)	(0.23)	(0.00)	(0.00)	(0.00)	(0.48)	(0.00)	(0.00)	(0.31)	(0.22)	(0.00)
UK-HO	0.1687	0.0565	0.1369	0.3554	-0.0278	0.0370	0.2087	0.9315	0.0038	-0.0011	0.9714
	(0.00)	(0.03)	(0.00)	(0.00)	(0.21)	(0.18)	(0.00)	(0.00)	(0.56)	(0.92)	(0.00)
UK-JAP	0.1553	0.1159	0.2768	0.3228	-0.0273	-0.0366	0.2839	0.9491	-0.0081	0.0375	0.9315
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.25)	(0.00)	(0.00)	(0.26)	(0.01)	(0.00)
HO-JAP	0.1484	0.2268	0.1931	0.2193	0.0329	0.0133	0.2848	0.9826	-0.0256	0.0141	0.9308

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Table: 4.2 Continued from previous page

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.62)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)
Emerging-Emerging (E-E) combination											
BR-RUS	0.3452	0.3583	0.0559	0.2272	0.0096	0.0670	0.2972	0.9595	-0.0032	-0.0344	0.9472
	(0.00)	(0.00)	(0.57)	(0.00)	(0.56)	(0.02)	(0.00)	(0.00)	(0.53)	(0.00)	(0.00)
BR-IND	0.3028	0.2315	0.4018	0.2315	-0.0072	0.0501	0.3398	0.9644	-0.0085	-0.0048	0.9021
	(0.00)	(0.00)	(0.00)	(0.00)	(0.77)	(0.03)	(0.00)	(0.00)	(0.43)	(0.58)	(0.00)
BR-CH	0.3684	-0.0171	0.1764	0.2523	-0.0672	-0.0156	0.2162	0.9485	0.0193	0.0050	0.9714
	(0.00)	(0.53)	(0.00)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)
RUS-IND	0.4045	0.2145	0.1327	0.3692	-0.0220	0.0921	0.1950	0.9227	-0.0081	-0.0326	0.9704
	(0.00)	(0.00)	(0.00)	(0.00)	(0.49)	(0.00)	(0.00)	(0.00)	(0.54)	(0.00)	(0.00)
RUS-CH	0.3429	-0.0072	0.1613	0.3364	-0.0785	-0.0070	0.1936	0.9327	0.0170	0.0045	0.9764
	(0.00)	(0.80)	(0.00)	(0.00)	(0.00)	(0.44)	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)
IND-CH	0.4464	0.0058	0.1701	0.3575	-0.0450	-0.0256	0.2153	0.9030	0.0208	0.0061	0.9718
	(0.00)	(0.85)	(0.00)	(0.00)	(0.01)	(0.09)	(0.00)	(0.00)	(0.01)	(0.35)	(0.00)
Developed-Emerging (D-E) combination											
US-BR	-0.1458	-0.2266	0.1052	0.2737	0.0024	0.0408	0.2005	0.9582	-0.0022	-0.0136	0.9741
	(0.00)	(0.00)	(0.00)	(0.00)	(0.84)	(0.19)	(0.00)	(0.00)	(0.49)	(0.09)	(0.00)
US-RUS	-0.1445	-0.1029	0.2694	0.2608	-0.0087	0.0005	0.2981	0.9598	0.0025	0.0005	0.9488
	(0.00)	(0.02)	(0.00)	(0.00)	(0.34)	(0.99)	(0.00)	(0.00)	(0.43)	(0.96)	(0.00)
US-IND	0.1538	0.2375	0.3303	0.2682	-0.0014	0.0554	0.2943	0.9599	-0.0073	-0.011	0.9277
	(0.00)	(0.00)	(0.00)	(0.00)	(0.91)	(0.04)	(0.00)	(0.00)	(0.18)	(0.24)	(0.00)
US-CH	-0.1565	-0.02	0.1712	0.2719	-0.0021	-0.0096	0.2012	0.9556	0.001	0.0013	0.9751
	(0.00)	(0.54)	(0.00)	(0.00)	(0.86)	(0.57)	(0.00)	(0.00)	(0.77)	(0.81)	(0.00)
UK-BR	-0.1619	-0.1878	0.1618	0.3467	-0.0208	0.1522	0.1677	0.9364	0.001	-0.0413	0.9786
	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.79)	(0.00)	(0.00)
UK-RUS	-0.158	-0.1991	0.1772	0.3088	0.0105	0.0641	0.2843	0.9446	-0.0027	-0.0297	0.9567
	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.04)	(0.00)	(0.00)	(0.28)	(0.00)	(0.00)
UK-IND	-0.1553	-0.2068	0.4253	0.3007	0.0015	-0.0675	0.3646	0.9524	-0.0094	0.0412	0.8923
	(0.00)	(0.00)	(0.00)	(0.00)	(0.90)	(0.10)	(0.00)	(0.00)	(0.12)	(0.02)	(0.00)
UK-CH	-0.1576	0.023	0.161	0.3282	-0.0071	0.0088	0.1908	0.9384	0.0044	-0.0018	0.9775
	(0.00)	(0.52)	(0.00)	(0.00)	(0.48)	(0.62)	(0.00)	(0.00)	(0.16)	(0.77)	(0.00)
HO-BR	-0.164	-0.2269	0.224	0.227	0.0304	-0.0182	0.229	0.9707	-0.0121	0.0044	0.9606
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.49)	(0.00)	(0.00)	(0.01)	(0.55)	(0.00)
HO-RUS	0.1579	0.2194	0.2539	0.2335	0.0225	0.0269	0.3118	0.9695	-0.0068	-0.0092	0.9423
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.48)	(0.00)	(0.00)	(0.05)	(0.44)	(0.00)
HO-IND	-0.0001	0.0649	0.3974	0.1668	0.0728	-0.2653	0.4389	1.0069	-0.0546	0.1221	0.8420
	(1.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HO-CH	0.1543	0.0051	0.1685	0.2667	-0.0407	-0.0241	0.2133	0.9595	0.0107	0.0076	0.9716
	(0.00)	(0.88)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)	(0.01)	(0.05)	(0.00)
JAP-BR	0.2660	0.0846	0.2505	0.3027	-0.0038	0.0654	0.1904	0.9391	0.0049	-0.0262	0.9744
	(0.00)	(0.16)	(0.00)	(0.00)	(0.85)	(0.01)	(0.00)	(0.00)	(0.54)	(0.00)	(0.00)
JAP-RUS	0.2601	0.1511	0.3266	0.2636	0.0398	0.0121	0.3199	0.9532	-0.0159	0.0016	0.9370
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.62)	(0.00)	(0.00)	(0.01)	(0.90)	(0.00)
JAP-IND	0.1804	-0.2857	0.0880	0.2205	0.1054	-0.1497	0.3425	0.9781	-0.0574	0.1105	0.8952
	(0.00)	(0.01)	(0.79)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JAP-CH	0.3143	-0.0229	0.1732	0.3168	-0.0150	0.0017	0.2070	0.9299	0.0086	0.0030	0.9732
	(0.00)	(0.44)	(0.00)	(0.00)	(0.27)	(0.91)	(0.00)	(0.00)	(0.05)	(0.59)	(0.00)

Note: $p-$values are given in parenthesis.

4.4.1.3 *VAR-BTGARCH-M*

This model differs from the preceding VAR-BGARCH-M model only in that the conditional volatility is now taken to be asymmetric due to leverage effect, which is very often the case in stock markets. The estimates of all the parameters of this model are presented in Table 4.3. We note from the entries of the table that the estimates of the parameters here are more or less the same as obtained for the VAR parameters in the preceding model. More explicitly, the mean spillover effects are, by and large, similar and hence we do not report these in any further detail here. Insofar as the transmission channels from the risk of one country to the mean return of another country - both direct and indirect - are concerned, the findings are, once again, almost the same as found in the VAR-BGARCH-M model. Hence, we discuss below only the spillovers of variances and covariances.

The first observation in this regards is that in 25 pairs of markets (out of the total of 28), the relevant parameters representing spillovers in the asymmetric components of H_t *viz.*, d_{12} and d_{21}, are either or both significant. In other words, there are only 3 pairs of countries where there is no spillover effects in asymmetric components of the variance. These countries are Brazil-China in E-E combination and US-India and UK-China in D-E combination. Moreover the number of significant pairs are 6, 5 and 14 in D-D , E-E and D-E combinations, respectively. It may also be noted that each of d_{11} and d_{22} parameters is significant for all the 28 pairs. Thus, summing up, it can be stated that in this bivariate modelling framework, the prevalence of asymmetric spillover is almost sure irrespective of the combination of markets from consideration of developed and emerging countries. In order to find the direction of the spillover, we note, from this table, that in the D-D combination of countries, the spillovers from UK to Hong Kong, Hong Kong to US, Japan to US, Japan to UK and Japan to Hong Kong are absent; in all other cases in this combination transmission channel is valid at least in one direction. It is thus noted that the spillovers from Japan to other developed economies are absent. Hence, it is a better portfolio choice for the US or the UK investors to invest in Japan when their stock markets crash. In the E-E combination, the numbers of pairs in the two directions where this channel is statistically insignificant are 2 each i.e., d_{12} is insignificant for Brazil- India and Brazil - China, and d_{21} is insignificant for Brazil-China and Russia-China. Finally, in D-E combination, this spillover is present in 10 pairs from the direction of developed to emerging and in 5 pairs from emerging to developed. This finding is on the expected line, since the stock markets of emerging economies are likely to be more affected by the presence of leverage effect in the developed economies than the same from the reverse direction. The 5 pairs of markets where the leverage effect of emerging economies affect those of the developed economies are: China-US, China - Hong Kong, Russia - Japan, Russia - US, and India - Japan. These show the relative importance of Russia and China among the four emerging countries considered in this study insofar as the influences of their stock markets on those of the developed economies are concerned. As regards the spillover effects of the symmetric component of H_t in this model, we note that the relevant coefficients i.e., α_{12}, α_{21}, β_{12}, β_{21}, are significant in most of the 28 pairs of countries. One pertinent observation is that in 3 countries *viz.*, Brazil-China, US-India, and UK-China where spillover effects in the asymmetric component are absent, the spillovers in the symmetric component of variance are, however, statistically significant.

Table 4.3: Estimates of the parameters of VAR-BTGARCH-M model

A: Parameters in the conditional mean part												
	Parameters in the VAR component						Parameters in the BTGARCH-in-mean compnent					
	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}	λ_{11}	λ_{12}	λ_{13}	λ_{21}	λ_{22}	λ_{23}
Developed-Developed (D-D) combination												
US-UK	0.0342	0.0463	-0.0961	0.3219	0.0459	-0.2422	0.154	-0.1031	0.0866	0.3402	-0.2128	-0.0992
	(0.23)	(0.08)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)	(0.04)	(0.49)	(0.00)	(0.00)	(0.12)
US-HO	0.0413	0.0642	-0.0822	0.4738	0.0225	-0.1050	0.0329	-0.0312	-0.0163	0.0119	-0.0118	0.0250
	(0.11)	(0.04)	(0.00)	(0.00)	(0.11)	(0.00)	(0.07)	(0.07)	(0.71)	(0.81)	(0.49)	(0.31)
US-JAP	0.0359	0.0199	-0.0888	0.5028	0.0223	-0.0804	0.0320	-0.0589	-0.0487	-0.0025	-0.0001	0.0416
	(0.27)	(0.59)	(0.00)	(0.00)	(0.11)	(0.00)	(0.21)	(0.02)	(0.35)	(0.97)	(0.99)	(0.06)
UK-HO	0.0454	0.0670	-0.0643	0.3452	0.0131	-0.1221	0.0695	-0.0162	-0.0828	-0.0279	-0.0040	0.0205
	(0.12)	(0.08)	(0.00)	(0.00)	(0.33)	(0.00)	(0.03)	(0.54)	(0.19)	(0.69)	(0.82)	(0.43)
UK-JAP	0.0298	-0.0194	-0.0492	0.3870	0.0180	-0.1138	0.0216	-0.0698	-0.0573	-0.0908	0.0186	0.0974
	(0.21)	(0.69)	(0.01)	(0.00)	(0.18)	(0.00)	(0.30)	(0.01)	(0.13)	(0.10)	(0.23)	(0.00)
HO-JAP	0.1416	0.1052	0.0156	0.0804	-0.0255	-0.0380	-0.0866	-0.0873	0.1635	0.1203	-0.0341	-0.0079
	(0.01)	(0.07)	(0.48)	(0.00)	(0.20)	(0.09)	(0.06)	(0.03)	(0.06)	(0.16)	(0.30)	(0.84)
Emerging-Emerging (E-E) combination												
BR-RUS	0.0270	0.2132	-0.0390	0.1869	0.0202	-0.0575	0.0339	-0.0116	0.0107	-0.0259	-0.0120	0.0070
	(0.68)	(0.01)	(0.04)	(0.00)	(0.20)	(0.00)	(0.17)	(0.63)	(0.74)	(0.53)	(0.29)	(0.67)
BR-IND	0.0892	0.2263	-0.0500	0.1201	0.0390	0.0054	0.0275	-0.0273	0.0212	0.0015	-0.0275	0.0092
	(0.23)	(0.00)	(0.01)	(0.00)	(0.05)	(0.79)	(0.22)	(0.13)	(0.61)	(0.97)	(0.08)	(0.66)
BR-CH	0.0198	-0.0675	-0.0167	0.0768	0.0082	-0.0246	0.0208	0.0034	0.0027	-0.0702	0.0015	0.0382
	(0.81)	(0.30)	(0.31)	(0.00)	(0.48)	(0.09)	(0.32)	(0.81)	(0.96)	(0.13)	(0.93)	(0.05)
RUS-IND	0.2057	0.1569	0.0031	0.0695	0.0091	-0.0156	0.0247	-0.0090	-0.0678	0.0006	-0.0147	0.0089
	(0.00)	(0.00)	(0.88)	(0.00)	(0.69)	(0.41)	(0.08)	(0.34)	(0.09)	(0.98)	(0.51)	(0.65)
RUS-CH	0.2248	-0.0686	0.0059	0.0467	-0.0228	-0.0193	0.0041	0.0019	-0.1076	-0.0083	-0.0110	0.0264
	(0.00)	(0.18)	(0.75)	(0.00)	(0.20)	(0.29)	(0.68)	(0.71)	(0.02)	(0.76)	(0.53)	(0.17)
IND-CH	0.2062	-0.0791	0.0563	0.0160	-0.0081	-0.0162	-0.0046	0.0072	0.0230	-0.1040	-0.0168	0.0503
	(0.00)	(0.17)	(0.01)	(0.31)	(0.62)	(0.41)	(0.80)	(0.52)	(0.66)	(0.04)	(0.31)	(0.02)
Developed-Emerging (D-E) combination												
US-BR	0.0722	0.0068	-0.0791	0.0439	0.0019	-0.0245	0.0157	0.0134	0.0437	0.0027	-0.0288	0.0192
	(0.10)	(0.92)	(0.00)	(0.05)	(0.87)	(0.18)	(0.62)	(0.79)	(0.30)	(0.97)	(0.11)	(0.54)
US-RUS	0.0603	0.1858	-0.0848	0.2925	-0.0039	-0.0486	0.0493	-0.0634	-0.016	0.0288	-0.0106	0.0064
	(0.01)	(0.00)	(0.00)	(0.00)	(0.71)	(0.01)	(0.05)	(0.05)	(0.63)	(0.58)	(0.01)	(0.58)
US-IND	0.0493	0.1608	-0.0897	0.263	0.001	-0.0042	0.0185	-0.0273	0.0013	0.0076	-0.0048	0.0054
	(0.14)	(0.00)	(0.00)	(0.00)	(0.93)	(0.83)	(0.37)	(0.16)	(0.96)	(0.87)	(0.61)	(0.78)
US-CH	0.0797	-0.0551	-0.0775	0.1422	0.0091	-0.0129	0.0292	-0.0092	0.013	-0.0193	-0.0248	0.0355
	(0.00)	(0.19)	(0.00)	(0.00)	(0.39)	(0.38)	(0.06)	(0.51)	(0.73)	(0.79)	(0.00)	(0.02)
UK-BR	0.1123	0.0541	-0.1249	0.0458	0.0874	-0.0538	0.0579	-0.0236	0.0055	-0.0058	-0.037	0.026
	(0.01)	(0.45)	(0.00)	(0.13)	(0.00)	(0.01)	(0.12)	(0.64)	(0.90)	(0.93)	(0.02)	(0.35)
UK-RUS	0.0774	0.1853	-0.053	0.0106	0.0123	0.0055	0.0343	-0.023	-0.0046	-0.0273	-0.0091	0.0099
	(0.00)	(0.00)	(0.00)	(0.73)	(0.19)	(0.78)	(0.03)	(0.46)	(0.82)	(0.56)	(0.12)	(0.45)
UK-IND	0.0555	0.1757	-0.0643	0.1472	0.0305	0.0102	0.025	-0.0544	-0.0146	0.0384	-0.0059	0.0093
	(0.05)	(0.00)	(0.00)	(0.00)	(0.01)	(0.55)	(0.30)	(0.01)	(0.72)	(0.41)	(0.43)	(0.61)
UK-CH	0.081	-0.0635	-0.0509	0.1105	0.0048	-0.0194	0.031	-0.0094	-0.0299	-0.0445	-0.0181	0.0411
	(0.02)	(0.20)	(0.00)	(0.00)	(0.66)	(0.22)	(0.03)	(0.53)	(0.31)	(0.46)	(0.06)	(0.02)
HO-BR	0.1014	-0.0427	-0.0748	0.0619	0.2254	-0.0575	0.0038	0.0213	0.0164	-0.0859	-0.02	0.0515
	(0.11)	(0.62)	(0.00)	(0.01)	(0.00)	(0.00)	(0.87)	(0.34)	(0.70)	(0.09)	(0.34)	(0.09)
HO-RUS	0.0592	0.166	-0.0634	0.0329	0.0959	-0.0173	0.0254	0.0057	-0.026	-0.0861	-0.0017	0.0214
	(0.10)	(0.00)	(0.00)	(0.19)	(0.00)	(0.33)	(0.12)	(0.75)	(0.30)	(0.00)	(0.82)	(0.08)
HO-IND	0.0503	0.1975	-0.0269	0.0743	0.0594	-0.0050	0.0013	-0.1195	0.0101	0.1494	0.0070	0.0050
	(0.19)	(0.00)	(0.20)	(0.00)	(0.00)	(0.83)	(0.96)	(0.00)	(0.83)	(0.01)	(0.65)	(0.82)

Continued on next page

Table: 4.3 Continued from previous page

	a_1	a_2	b_{11}	b_{21}	b_{12}	b_{22}	λ_{11}	λ_{12}	λ_{13}	λ_{21}	λ_{22}	λ_{23}
HO-CH	0.0434	-0.0840	0.0115	0.0219	-0.0156	0.0014	0.0165	0.0195	0.0010	-0.0767	-0.0044	0.0474
	(0.31)	(0.10)	(0.55)	(0.18)	(0.33)	(0.93)	(0.37)	(0.15)	(0.98)	(0.07)	(0.77)	(0.03)
JAP-BR	0.2383	0.0873	-0.0653	0.0355	0.2314	-0.0289	0.0307	-0.0022	0.0892	0.0361	-0.0888	-0.0005
	(0.00)	(0.35)	(0.00)	(0.10)	(0.00)	(0.11)	(0.20)	(0.93)	(0.07)	(0.53)	(0.00)	(0.99)
JAP-RUS	0.0564	0.1285	-0.0589	0.0098	0.1317	0.0022	0.0326	0.0400	-0.0375	-0.0877	-0.0085	0.0093
	(0.16)	(0.05)	(0.00)	(0.59)	(0.00)	(0.91)	(0.10)	(0.10)	(0.14)	(0.09)	(0.26)	(0.49)
JAP-IND	0.0277	0.1748	-0.0315	0.0267	0.0847	0.0265	0.0047	-0.0073	-0.0280	0.0155	0.0072	-0.0042
	(0.53)	(0.00)	(0.06)	(0.13)	(0.00)	(0.12)	(0.87)	(0.72)	(0.52)	(0.73)	(0.66)	(0.85)
JAP-CH	0.1046	-0.1345	0.0093	0.0066	-0.0357	-0.0057	0.0059	0.0327	-0.0336	-0.1747	-0.0150	0.0627
	(0.09)	(0.03)	(0.54)	(0.60)	(0.01)	(0.68)	(0.80)	(0.06)	(0.54)	(0.00)	(0.27)	(0.00)

B: Parameters in the BTGARCH part

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	d_{11}	d_{12}	d_{21}	d_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Developed-Developed (D-D) combination															
US-UK	0.149	0.084	0.121	-0.135	0.154	0.143	-0.007	0.286	0.109	0.068	0.321	0.956	-0.006	0.010	0.936
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.84)	(0.00)	(0.01)	(0.08)	(0.00)	(0.00)	(0.66)	(0.30)	(0.00)
US-HO	0.136	0.098	0.202	0.097	-0.132	0.208	-0.060	0.331	0.060	-0.092	0.361	0.954	-0.020	0.006	0.943
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.45)	(0.00)	(0.11)	(0.03)	(0.00)	(0.00)	(0.02)	(0.43)	(0.00)
US-JAP	0.155	0.059	0.316	0.010	-0.060	0.169	0.150	0.375	0.014	-0.073	0.320	0.952	0.002	0.026	0.916
	(0.00)	(0.19)	(0.00)	(0.75)	(0.01)	(0.00)	(0.00)	(0.00)	(0.50)	(0.03)	(0.00)	(0.00)	(0.82)	(0.01)	(0.00)
UK-HO	0.144	0.071	0.181	0.092	-0.088	0.131	0.094	0.371	0.037	0.038	0.271	0.940	0.008	-0.013	0.961
	(0.00)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)	(0.06)	(0.19)	(0.00)	(0.00)	(0.23)	(0.18)	(0.00)
UK-JAP	0.159	0.114	0.254	-0.115	0.032	0.042	0.234	0.407	-0.027	0.088	0.229	0.951	-0.009	0.026	0.924
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.14)	(0.00)	(0.00)	(0.35)	(0.01)	(0.00)	(0.00)	(0.15)	(0.01)	(0.00)
HO-JAP	0.158	0.102	0.269	-0.195	0.130	-0.129	0.275	0.297	0.046	0.066	0.279	0.974	-0.033	0.027	0.914
	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.07)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Emerging-Emerging (E-E) combination															
BR-RUS	0.325	0.354	0.000	-0.086	0.129	-0.014	0.278	0.325	-0.105	0.108	0.197	0.957	-0.003	-0.040	0.946
	(0.00)	(0.00)	(1.00)	(0.00)	(0.00)	(0.60)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)
BR-IND	0.397	0.293	0.301	0.051	-0.112	0.186	0.046	0.330	0.013	0.080	0.447	0.946	-0.005	-0.030	0.892
	(0.00)	(0.00)	(0.00)	(0.20)	(0.00)	(0.00)	(0.40)	(0.00)	(0.74)	(0.02)	(0.00)	(0.00)	(0.73)	(0.02)	(0.00)
BR-CH	0.359	0.030	0.190	-0.035	-0.025	-0.003	0.231	0.344	-0.042	0.021	0.066	0.951	0.017	-0.006	0.967
	(0.00)	(0.39)	(0.00)	(0.52)	(0.24)	(0.82)	(0.00)	(0.00)	(0.17)	(0.27)	(0.29)	(0.00)	(0.01)	(0.20)	(0.00)
RUS-IND	0.406	0.340	0.267	-0.289	0.120	-0.032	0.054	0.318	0.093	0.129	0.422	0.928	-0.053	-0.022	0.906
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
RUS-CH	0.352	0.047	0.194	-0.236	-0.013	-0.007	0.180	0.328	-0.113	-0.002	0.200	0.934	0.020	-0.004	0.968
	(0.00)	(0.18)	(0.00)	(0.00)	(0.54)	(0.61)	(0.00)	(0.00)	(0.00)	(0.90)	(0.00)	(0.00)	(0.00)	(0.35)	(0.00)
IND-CH	0.439	-0.002	0.208	0.147	-0.071	0.010	0.250	0.510	-0.063	0.082	-0.095	0.887	0.049	-0.025	0.964
	(0.00)	(0.97)	(0.00)	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)	(0.06)	(0.00)	(0.08)	(0.00)	(0.00)	(0.01)	(0.00)
Developed-Emerging (D-E) combination															
US-BR	0.143	0.232	0.106	0.061	0.002	-0.101	0.193	0.334	0.011	0.118	0.172	0.964	-0.003	-0.007	0.968
	(0.00)	(0.00)	(0.00)	(0.04)	(0.90)	(0.00)	(0.00)	(0.00)	(0.48)	(0.01)	(0.00)	(0.00)	(0.36)	(0.37)	(0.00)
US-RUS	0.157	0.072	0.269	0.029	-0.011	-0.124	0.319	0.354	0.022	0.054	0.134	0.953	0.003	0.022	0.938
	(0.00)	(0.06)	(0.00)	(0.20)	(0.26)	(0.00)	(0.00)	(0.00)	(0.02)	(0.14)	(0.00)	(0.00)	(0.28)	(0.02)	(0.00)
US-IND	0.158	0.180	0.405	0.001	-0.042	0.242	0.132	0.370	0.008	0.069	0.427	0.955	-0.004	-0.002	0.883
	(0.00)	(0.00)	(0.00)	(0.98)	(0.05)	(0.00)	(0.00)	(0.00)	(0.66)	(0.28)	(0.00)	(0.00)	(0.52)	(0.88)	(0.00)
US-CH	0.144	0.007	0.192	-0.001	-0.002	-0.012	0.239	0.374	0.035	0.025	-0.089	0.953	0.008	-0.002	0.964
	(0.00)	(0.86)	(0.00)	(0.97)	(0.83)	(0.50)	(0.00)	(0.00)	(0.01)	(0.33)	(0.03)	(0.00)	(0.02)	(0.81)	(0.00)
UK-BR	0.136	0.173	0.177	0.051	-0.055	-0.053	0.155	0.408	-0.009	0.202	0.149	0.943	0.007	-0.022	0.973
	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.16)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)	(0.00)	(0.06)	(0.02)	(0.00)
UK-RUS	0.161	0.218	0.189	0.047	0.023	-0.158	0.290	0.392	0.003	0.158	0.206	0.952	-0.005	-0.015	0.946
	(0.00)	(0.00)	(0.00)	(0.06)	(0.02)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)	(0.00)	(0.05)	(0.10)	(0.00)
UK-IND	0.146	0.136	0.395	0.142	-0.071	0.239	0.146	0.381	0.014	-0.185	0.512	0.943	0.001	0.026	0.876
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.00)	(0.90)	(0.04)	(0.00)
UK-CH	0.135	-0.029	0.193	0.048	-0.027	0.007	0.237	0.386	0.029	0.031	0.065	0.948	0.011	-0.007	0.965
	(0.00)	(0.39)	(0.00)	(0.05)	(0.01)	(0.67)	(0.00)	(0.00)	(0.12)	(0.15)	(0.08)	(0.00)	(0.00)	(0.17)	(0.00)
HO-BR	0.207	0.271	0.295	-0.153	-0.057	-0.004	0.061	0.302	0.004	0.142	0.279	0.954	-0.011	-0.004	0.946

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Table: 4.2 Continued from previous page

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	d_{11}	d_{12}	d_{21}	d_{22}	β_{11}	β_{12}	β_{21}	β_{22}
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.93)	(0.33)	(0.00)	(0.89)	(0.00)	(0.00)	(0.00)	(0.10)	(0.64)	(0.00)
HO-RUS	0.233	0.201	0.293	-0.081	0.036	-0.061	0.300	0.349	0.018	0.129	0.223	0.957	-0.008	-0.011	0.930
	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.03)	(0.00)	(0.00)	(0.22)	(0.00)	(0.00)	(0.00)	(0.20)	(0.28)	(0.00)
HO-IND	0.198	0.237	0.265	-0.033	-0.062	0.280	-0.231	0.371	-0.020	0.218	0.277	0.976	-0.037	0.027	0.887
	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.56)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)
HO-CH	0.197	0.013	0.181	0.129	-0.027	0.006	0.208	0.354	-0.076	0.012	0.119	0.953	0.015	-0.002	0.969
	(0.00)	(0.59)	(0.00)	(0.00)	(0.06)	(0.67)	(0.00)	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)	(0.00)	(0.63)	(0.00)
JAP-BR	0.269	-0.061	0.348	0.109	-0.117	0.129	0.110	0.353	0.016	0.061	0.282	0.925	0.033	-0.045	0.954
	(0.00)	(0.35)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.49)	(0.08)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JAP-RUS	0.298	0.059	0.319	-0.081	0.000	-0.097	0.313	0.362	0.032	0.107	0.178	0.935	0.011	-0.023	0.937
	(0.00)	(0.24)	(0.00)	(0.00)	(0.98)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.03)	(0.04)	(0.00)
JAP-IND	0.272	0.049	0.391	-0.040	-0.076	0.270	-0.058	0.350	0.057	0.060	0.482	0.952	-0.026	0.039	0.869
	(0.00)	(0.35)	(0.00)	(0.30)	(0.01)	(0.00)	(0.24)	(0.00)	(0.05)	(0.11)	(0.00)	(0.00)	(0.05)	(0.04)	(0.00)
JAP-CH	0.328	-0.034	0.189	0.010	-0.029	-0.011	0.223	0.424	-0.037	0.039	0.132	0.931	0.019	-0.006	0.965
	(0.00)	(0.29)	(0.00)	(0.93)	(0.10)	(0.54)	(0.00)	(0.00)	(0.27)	(0.08)	(0.00)	(0.00)	(0.00)	(0.33)	(0.00)

Note: $p-$values are given in parenthesis.

4.4.2 Results of estimation of the proposed model

We now discuss about the results of estimation of the proposed model, called the TVAR-BTGARCH-M model, which is specified in equations (4.4) and (4.6). As already discussed, the introduction of market movements - up and down - and studying their effects on the risk-return relationship in bivariate returns set-up, have been considered in the proposed model. In the proposed model, the risk has been taken to be asymmetric i.e., the asymmetric version of the BEKK model given in equation (4.4), and the results of this models are presented in Table 4.5. However, before we do that, we present the results of another model which takes the usual (symmetric) GARCH model in the bivariate case along with the two markets movements - up and down. The results of this model which has been designated as TVAR-BGARCH-M nodel, are presented in Table 4.4.

4.4.2.1 TVAR-BGARCH-M model

It may be noted that this model as well as the proposed TVAR-BTGARCH-M model consider two market movements, up and down, and these are characterised, as mentioned in Section 4.2 of this chapter and also in Section 3 of Chapter 3, by the average value of the past k returns being positive and non-positive, respectively. The choice of the value of k has been taken as 20 since in the univariate study carried out in the preceding chapter, $k = 20$ was found to be an optimum choice for most of the returns series.

Since in this model, introduction of two regimes characterized by two market movements - down and up[6] - is the distinctive feature, we first discuss the estimates of the conditional mean part of the model.

[6] These two market movements are being indicated, in notations, by superscripts 1 and 2, wherever applicable. Further,

We first take the 8 pairs under D-D combination. We note that the numbers of own-dependences in terms of first lag coefficients for the two return series, b_{11}^1,b_{11}^2, b_{22}^1 and b_{22}^2, are significant in 5, 4, 6 and 5 pairs, respectively, showing that the returns are significantly correlated with their own past for each of the two regimes. Now, insofar as mean spillovers across the two market conditions are concerned, the relevant coefficients *viz.* b_{21}^1 ,b_{12}^2, b_{21}^2 and b_{12}^2 are significant in 6, 5, 3 and 1 pairs, respectively. Thus it is seen that among the developed stock markets the spillover effects are found to be responsive to down and up market conditions. It may be noted that there are few pairs of countries where this spillover effect is not significant. These countries (from the direction of 2nd country to 1st country) are: US-Hong Kong, UK-Hong Kong, and Hong Kong-Japan in down market, and US-UK, US-Hong Kong, US-Japan, UK-Hong Kong, and UK-Japan in up market.

In case of 6 pairs of countries in E-E combination, the findings are more or less similar as in D-D combination. While the own dependences are significant for both the regimes in most cases, the figures for mean spillovers across regimes, as represented by the parameters b_{21}^1 ,b_{12}^2, b_{21}^2 and b_{12}^2, are 5, 5, 2 and 1, respectively. Thus it is established that in these pairs of countries the two market conditions play significant roles insofar as the mean spillover is concerned. It may be noted that there are few pairs in this combination (from the direction of 2nd country to 1st country) *viz.*, Brazil - China, India - Russia, Russia- China and India-China in down market, and Brazil-Russia, Brazil-India, Brazil-China, Russia-India and India-China in up market where the spillover coefficients are insignificant, suggesting that the stock markets of these countries are not affected by the transmission channel of mean. Final observation in this case is that India-China does not have spillover effect in any of the regimes in both the directions.

The own lag dependences of the two returns series in the model are found to be, as expectedly, significant in many of the 16 pairs in the D-E combination. For instance, b_{11}^1 ,b_{11}^2, b_{22}^1 and b_{22}^2 are significant in 13, 9, 4 and 4 pairs, respectively. Talking about the mean spillover effects, we first note that all the significant spillovers in both market conditions have been found to be positive. Now, insofar as the number of significant spillovers from developed to emerging markets when both markets conditions are taken together, is concerned, it is 14 while the same from emerging to developed is 11. These figures in the two market conditions separately, down and up, are 6 and 11, respectively, from developed to emerging while these numbers are 8 and 10, respectively, from emerging to developed economies. This shows that in D-E combination of pairs, the up and down market conditions in case of mean spillover

these two market conditions would also be referred to as regime 1 and regime 2, respectively, whenever it is so convenient.

play a significant role and hence expectedly in the risk-return relationship as well. Whether this spillover effects across the two regimes are significant is an important empirical question, and the underlying null hypothesis has been tested the results are reported in the next section. It may be worth noting that the number of significant mean spillover cases in the VAR-BGARCH-M model have been found to be 9 in each of the two directions of spillovers. There are only two cases *viz.*, UK-Russia and Hong Kong-China where no spillovers in any of the two market conditions were found.

The conditional variance-covariance model is symmetric here and hence the variance-covariance spillover effects, are likely to be somewhat similar to what have been obtained in case of the VAR-BGARCH-M model in Section (4.4.1.2). However, the BGARCH-M effect would now be influenced by the presence of up and down market conditions.

Table 4.4: Estimates of the parameters of TVAR-BGARCH-M model

A: Parameters in the conditional mean part of down market												
	VAR in down market						BGARCH-in-mean in down market					
	a_1^1	a_2^1	b_{11}^1	b_{21}^1	b_{12}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
Developed-Developed (D-D) combination												
US-UK	0.0594	0.0540	-0.1610	0.3539	0.0493	-0.2633	0.0146	-0.0012	0.1419	-0.0466	-0.1133	0.0735
	(0.15)	(0.18)	(0.00)	(0.00)	(0.09)	(0.00)	(0.78)	(0.98)	(0.05)	(0.60)	(0.09)	(0.34)
US-HO	0.0579	0.0546	-0.1009	0.4848	0.0181	-0.1464	0.0528	-0.0353	-0.0348	0.0145	-0.0179	0.0255
	(0.08)	(0.09)	(0.00)	(0.00)	(0.35)	(0.00)	(0.03)	(0.05)	(0.34)	(0.66)	(0.24)	(0.19)
US-JAP	0.0410	-0.0632	-0.1275	0.5049	0.0376	-0.0712	0.0433	-0.0479	-0.0623	-0.0041	-0.0012	0.0569
	(0.22)	(0.05)	(0.00)	(0.00)	(0.07)	(0.00)	(0.07)	(0.03)	(0.03)	(0.95)	(0.94)	(0.01)
UK-HO	0.0681	0.0556	-0.0557	0.3478	0.0058	-0.1744	0.0728	-0.0185	-0.0985	-0.0360	0.0169	0.0312
	(0.09)	(0.24)	(0.01)	(0.00)	(0.77)	(0.00)	(0.04)	(0.51)	(0.18)	(0.62)	(0.44)	(0.22)
UK-JAP	0.0250	-(0.13)	-0.0627	(0.39)	0.0459	-(0.12)	0.0156	-(0.05)	-0.0678	-(0.11)	0.0498	(0.12)
	(0.39)	(0.04)	(0.02)	(0.00)	(0.01)	(0.00)	(0.49)	(0.08)	(0.01)	(0.10)	(0.00)	(0.00)
HO-JAP	0.2567	(0.06)	-(0.03)	(0.13)	0.0244	-(0.08)	-(0.12)	-(0.09)	0.2462	(0.12)	-(0.08)	(0.00)
	(0.00)	(0.39)	(0.26)	(0.00)	(0.37)	(0.01)	(0.02)	(0.05)	(0.01)	(0.18)	(0.02)	(0.97)
Emerging-Emerging (E-E) combination												
BR-RUS	-0.0062	0.2463	-0.0808	0.1289	0.0385	-0.0588	0.0513	-0.0241	0.0054	-0.0018	-0.0161	0.0036
	(0.95)	(0.08)	(0.00)	(0.00)	(0.09)	(0.04)	(0.17)	(0.61)	(0.91)	(0.98)	(0.30)	(0.86)
BR-IND	0.0719	0.2316	-0.0925	0.1123	0.0575	-0.0069	0.0393	-0.0403	-0.0207	-0.0025	-0.0161	0.0209
	(0.51)	(0.03)	(0.00)	(0.00)	(0.02)	(0.76)	(0.19)	(0.08)	(0.70)	(0.96)	(0.43)	(0.39)
BR-CH	-0.0487	-0.1447	-0.0357	0.0609	-0.0132	-0.0188	0.0329	0.0024	-0.0134	-0.0328	0.0040	0.0471
	(0.54)	(0.06)	(0.03)	(0.00)	(0.64)	(0.40)	(0.13)	(0.90)	(0.62)	(0.62)	(0.85)	(0.05)
RUS-IND	0.2572	0.025	0.0011	0.1043	0.0233	-0.0634	0.0154	-0.0161	0.0076	0.0264	-0.0412	0.0262
	(0.01)	(0.64)	(0.96)	(0.00)	(0.37)	(0.01)	(0.33)	(0.18)	(0.87)	(0.51)	(0.13)	(0.20)
RUS-CH	0.222	-0.164	0.0037	0.0455	0.016	-0.0237	0.0064	0.0084	-0.0495	-0.0418	-0.0142	0.0377
	(0.05)	(0.00)	(0.88)	(0.00)	(0.64)	(0.29)	(0.59)	(0.24)	(0.49)	(0.30)	(0.60)	(0.11)
IND-CH	0.116	-0.1591	0.0361	0.0054	0.0045	-0.0065	0.0187	0.0076	0.0506	-0.1759	-0.0396	0.0768
	(0.00)	(0.01)	(0.18)	(0.79)	(0.86)	(0.80)	(0.36)	(0.60)	(0.43)	(0.01)	(0.11)	(0.00)
Developed-Emerging (D-E) combination												
US-BR	0.0674	-0.0481	-0.0900	0.0107	-0.0270	-0.0242	0.0398	0.0321	0.0136	-0.0320	-0.0233	0.0290
	(0.32)	(0.60)	(0.00)	(0.74)	(0.12)	(0.34)	(0.35)	(0.62)	(0.82)	(0.74)	(0.39)	(0.50)
US-RUS	0.0533	0.1866	-0.1383	0.2412	-0.0005	-0.0400	0.0875	-0.0387	-0.0504	0.0169	-0.0122	0.0037
	(0.13)	(0.02)	(0.00)	(0.00)	(0.96)	(0.13)	(0.00)	(0.39)	(0.09)	(0.82)	(0.04)	(0.81)
US-IND	0.0423	0.0353	-0.1278	0.2478	-0.0145	-0.0186	0.0353	-0.0217	-0.0471	-0.0211	0.0031	0.0281
	(0.32)	(0.68)	(0.00)	(0.00)	(0.38)	(0.35)	(0.11)	(0.26)	(0.07)	(0.66)	(0.74)	(0.19)

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Table: 4.4 Continued from previous page

	a_1^1	a_2^1	b_{11}^1	b_{21}^1	b_{12}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
US-CH	0.1017	-0.1263	-0.1114	0.1401	-0.0141	-0.0107	0.0293	-0.0209	0.0091	0.0862	-0.0310	0.0454
	(0.10)	(0.01)	(0.00)	(0.00)	(0.42)	(0.52)	(0.20)	(0.34)	(0.89)	(0.31)	(0.04)	(0.03)
UK-BR	0.1017	-0.0340	-0.1493	0.0196	0.0964	-0.0721	0.0811	0.0075	-0.0169	-0.0749	-0.0237	0.0526
	(0.10)	(0.66)	(0.00)	(0.52)	(0.00)	(0.00)	(0.04)	(0.90)	(0.76)	(0.38)	(0.23)	(0.09)
UK-RUS	0.1140	0.1344	-0.0473	0.0201	0.0121	-0.0047	0.0941	-0.0079	-0.0409	0.0013	-0.0091	0.0027
	(0.00)	(0.09)	(0.04)	(0.62)	(0.36)	(0.86)	(0.00)	(0.85)	(0.12)	(0.98)	(0.22)	(0.87)
UK-IND	0.1122	0.0875	-0.0539	0.1694	0.0205	-0.0670	0.0499	-0.0623	-0.0141	0.0676	-0.0111	0.0041
	(0.04)	(0.24)	(0.00)	(0.00)	(0.12)	(0.00)	(0.07)	(0.03)	(0.78)	(0.31)	(0.42)	(0.86)
UK-CH	0.0909	-0.1545	-0.0544	0.0859	-0.0254	-0.0156	0.0357	-0.0118	0.0177	-0.0200	-0.0108	0.0596
	(0.01)	(0.01)	(0.00)	(0.00)	(0.12)	(0.38)	(0.08)	(0.60)	(0.56)	(0.80)	(0.45)	(0.02)
HO-BR	0.1214	-0.1526	-0.1053	0.0167	0.2282	-0.0613	-0.0006	0.0436	0.0125	-0.1560	-0.0121	0.0867
	(0.20)	(0.24)	(0.00)	(0.62)	(0.00)	(0.02)	(0.98)	(0.17)	(0.80)	(0.02)	(0.66)	(0.05)
HO-RUS	0.0318	0.1905	-0.1016	0.0543	0.1137	-0.0175	0.0362	0.0015	-0.0208	-0.0697	-0.0035	0.0185
	(0.43)	(0.04)	(0.00)	(0.17)	(0.00)	(0.53)	(0.08)	(0.96)	(0.48)	(0.21)	(0.72)	(0.33)
HO-IND	0.1442	0.0987	-0.0762	0.0194	0.0844	0.0188	0.0121	0.0088	0.0405	-0.0087	-0.0168	0.0066
	(0.00)	(0.16)	(0.00)	(0.49)	(0.00)	(0.39)	(0.64)	(0.75)	(0.38)	(0.88)	(0.41)	(0.81)
HO-CH	0.0783	-0.1863	-0.0223	0.0086	-0.0292	0.0037	-0.0078	0.0343	0.0751	-0.1703	-0.0148	0.0901
	(0.28)	(0.00)	(0.39)	(0.71)	(0.21)	(0.88)	(0.71)	(0.08)	(0.08)	(0.01)	(0.48)	(0.00)
JAP-BR	0.1240	-0.0383	-0.0715	-0.0010	0.2626	-0.0458	0.0641	0.0252	0.0530	-0.0365	-0.0803	0.0204
	(0.19)	(0.62)	(0.00)	(0.98)	(0.00)	(0.06)	(0.01)	(0.49)	(0.27)	(0.30)	(0.00)	(0.52)
JAP-RUS	-0.0167	0.1573	-0.0562	0.0115	0.1429	0.0039	0.0664	0.0377	-0.0400	-0.0479	-0.0097	0.0033
	(0.73)	(0.16)	(0.02)	(0.70)	(0.00)	(0.87)	(0.01)	(0.43)	(0.26)	(0.41)	(0.32)	(0.86)
JAP-IND	0.0397	0.1874	-0.0278	0.1263	0.1151	-0.0273	0.0104	-0.0360	0.0549	0.0474	-0.0223	-0.0087
	(0.53)	(0.04)	(0.19)	(0.00)	(0.00)	(0.29)	(0.69)	(0.23)	(0.23)	(0.41)	(0.27)	(0.74)
JAP-CH	0.0189	-0.2168	0.0322	-0.0254	-0.0639	-0.0008	0.0298	0.0365	-0.0485	-0.2343	-0.0065	0.0923
	(0.81)	(0.01)	(0.19)	(0.24)	(0.01)	(0.96)	(0.20)	(0.18)	(0.51)	(0.01)	(0.74)	(0.00)

B: Parameters in the conditional mean part of up market												
	VAR in up market						BGARCH-in-mean in up market					
	a_1^2	a_2^1	b_{11}^2	b_{21}^2	b_{12}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
Developed-Developed (D-D) combination												
US-UK	0.0660	0.0714	-0.0102	0.3151	0.0066	-0.2172	-0.1297	-0.1023	0.1134	-0.0048	0.0447	0.0741
	(0.06)	(0.02)	(0.73)	(0.00)	(0.83)	(0.00)	(0.04)	(0.01)	(0.24)	(0.95)	(0.33)	(0.30)
US-HO	0.0395	0.0589	-0.0523	0.4631	0.0251	-0.0616	-0.0142	-0.0136	0.0314	-0.0057	-0.0050	0.0170
	(0.15)	(0.09)	(0.06)	(0.00)	(0.14)	(0.00)	(0.61)	(0.68)	(0.68)	(0.95)	(0.85)	(0.60)
US-JAP	0.0354	0.1029	-0.0388	0.5058	0.0081	-0.1006	-0.0005	-0.0429	-0.0120	-0.0825	0.0038	0.0140
	(0.18)	(0.01)	(0.10)	(0.00)	(0.62)	(0.00)	(0.99)	(0.36)	(0.88)	(0.54)	(0.86)	(0.68)
UK-HO	0.0764	0.0770	-0.0586	0.3535	0.0211	-0.0697	0.0178	-0.0317	-0.0387	0.0190	-0.0260	-0.0017
	(0.02)	(0.11)	(0.02)	(0.00)	(0.20)	(0.00)	(0.69)	(0.47)	(0.66)	(0.86)	(0.28)	(0.96)
UK-JAP	0.1132	(0.08)	-0.0291	(0.39)	-0.0025	-(0.11)	0.0151	-(0.10)	-0.0054	-(0.10)	-0.0499	(0.08)
	(0.00)	(0.11)	(0.25)	(0.00)	(0.88)	(0.00)	(0.46)	(0.02)	(0.92)	(0.21)	(0.03)	(0.07)
HO-JAP	0.0211	(0.14)	(0.06)	(0.03)	-0.0687	-(0.01)	-(0.12)	-(0.10)	0.1702	(0.15)	(0.04)	-(0.02)
	(0.74)	(0.04)	(0.03)	(0.24)	(0.01)	(0.71)	(0.02)	(0.04)	(0.08)	(0.11)	(0.35)	(0.67)
Emerging-Emerging (E-E) combination												
BR-RUS	0.0549	0.2343	-0.0082	0.2244	0.0050	-0.0516	0.0066	-0.0184	0.0194	-0.0632	-0.0029	0.0186
	(0.60)	(0.04)	(0.73)	(0.00)	(0.80)	(0.04)	(0.87)	(0.61)	(0.64)	(0.27)	(0.85)	(0.46)
BR-IND	0.1003	0.1908	-0.0119	0.1245	0.0152	0.0129	0.0163	0.0023	0.0962	0.0304	-0.0490	-0.0259
	(0.26)	(0.02)	(0.61)	(0.00)	(0.49)	(0.57)	(0.60)	(0.93)	(0.08)	(0.49)	(0.04)	(0.45)
BR-CH	0.0950	0.0698	0.0016	0.0946	0.0183	-0.0396	0.0021	-0.0067	0.0052	-0.1136	-0.0017	0.0263
	(0.37)	(0.17)	(0.90)	(0.00)	(0.14)	(0.10)	(0.93)	(0.69)	(0.88)	(0.09)	(0.92)	(0.27)
RUS-IND	0.2258	0.2083	0.0103	0.0446	0.0049	0.0196	0.0149	-0.0045	-0.1686	-0.004	0.0195	-0.0099
	(0.00)	(0.00)	(0.62)	(0.01)	(0.81)	(0.25)	(0.44)	(0.69)	(0.00)	(0.94)	(0.49)	(0.57)
RUS-CH	0.2802	0.0426	0.0114	0.0447	-0.0362	-0.025	-0.0093	-0.0034	-0.1565	0.0211	-0.0129	0.0118
	(0.00)	(0.30)	(0.60)	(0.00)	(0.01)	(0.35)	(0.58)	(0.68)	(0.01)	(0.58)	(0.55)	(0.56)
IND-CH	0.2709	0.0073	0.071	0.0202	-0.0154	-0.0373	-0.0283	0.0152	-0.0157	0.0455	-0.0075	0.0032
	(0.00)	(0.87)	(0.00)	(0.36)	(0.41)	(0.08)	(0.29)	(0.15)	(0.83)	(0.35)	(0.64)	(0.83)
Developed-Emerging (D-E) combination												

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Table: 4.4 Continued from previous page

	a_1^2	a_2^1	b_{11}^2	b_{21}^2	b_{12}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
US-BR	0.0813	-0.0156	-0.0497	0.0817	0.0198	-0.0407	0.0039	-0.0217	0.0384	0.0496	-0.0305	0.0275
	(0.03)	(0.78)	(0.06)	(0.01)	(0.19)	(0.10)	(0.92)	(0.72)	(0.36)	(0.50)	(0.04)	(0.24)
US-RUS	0.0637	0.2139	-0.0211	0.3314	-0.0107	-0.0512	-0.0242	-0.0991	0.0302	0.0172	-0.0045	0.0109
	(0.06)	(0.00)	(0.24)	(0.00)	(0.33)	(0.02)	(0.31)	(0.00)	(0.34)	(0.78)	(0.52)	(0.37)
US-IND	0.0836	0.2253	-0.0437	0.2750	0.0145	0.0047	-0.0009	-0.0047	0.0652	0.0057	-0.0300	-0.0259
	(0.06)	(0.00)	(0.06)	(0.00)	(0.36)	(0.84)	(0.97)	(0.88)	(0.41)	(0.94)	(0.06)	(0.21)
US-CH	0.0673	0.0553	-0.0356	0.1493	0.0188	-0.0268	0.0204	-0.0099	0.0156	-0.1603	-0.0218	0.0225
	(0.15)	(0.19)	(0.03)	(0.00)	(0.09)	(0.27)	(0.38)	(0.51)	(0.69)	(0.18)	(0.05)	(0.21)
UK-BR	0.1741	0.0652	-0.0843	0.0641	0.0810	-0.0367	0.0247	-0.0655	-0.0188	0.0809	-0.0507	0.0128
	(0.00)	(0.42)	(0.00)	(0.06)	(0.00)	(0.14)	(0.34)	(0.04)	(0.39)	(0.02)	(0.00)	(0.70)
UK-RUS	0.0917	0.2307	-0.0378	0.0054	0.0118	0.0111	-0.0608	-0.0313	0.0389	-0.0801	-0.0100	0.0158
	(0.00)	(0.00)	(0.05)	(0.87)	(0.30)	(0.63)	(0.02)	(0.36)	(0.10)	(0.08)	(0.14)	(0.33)
UK-IND	0.1052	0.1682	-0.0661	0.1326	0.0374	0.0224	-0.0595	-0.0208	0.0704	0.0888	-0.0256	-0.0219
	(0.00)	(0.00)	(0.01)	(0.00)	(0.01)	(0.32)	(0.04)	(0.28)	(0.22)	(0.05)	(0.04)	(0.22)
UK-CH	0.1169	0.0441	-0.0300	0.1416	0.0191	-0.0320	-0.0135	0.0048	-0.0902	-0.0905	-0.0239	0.0132
	(0.00)	(0.45)	(0.21)	(0.00)	(0.07)	(0.13)	(0.62)	(0.80)	(0.18)	(0.36)	(0.04)	(0.57)
HO-BR	0.1210	0.0231	-0.0371	0.0968	0.2259	-0.0493	0.0113	-0.0073	-0.0236	-0.0212	-0.0303	0.0294
	(0.09)	(0.83)	(0.11)	(0.00)	(0.00)	(0.02)	(0.63)	(0.78)	(0.51)	(0.75)	(0.25)	(0.46)
HO-RUS	0.0854	0.1713	-0.0268	0.0128	0.0845	-0.0142	0.0286	0.0093	-0.0629	-0.0855	-0.0024	0.0152
	(0.02)	(0.01)	(0.16)	(0.60)	(0.00)	(0.53)	(0.09)	(0.76)	(0.04)	(0.27)	(0.80)	(0.46)
HO-IND	0.0363	0.1434	0.0052	0.0470	0.0445	0.0270	0.0056	-0.0420	0.0537	0.2122	-0.0136	-0.0526
	(0.34)	(0.00)	(0.82)	(0.07)	(0.05)	(0.22)	(0.85)	(0.16)	(0.26)	(0.00)	(0.59)	(0.14)
HO-CH	0.0293	0.0452	0.0493	0.0304	-0.0077	-0.0137	0.0487	0.0008	-0.0935	0.0225	-0.0012	0.0036
	(0.57)	(0.53)	(0.00)	(0.22)	(0.64)	(0.57)	(0.01)	(0.96)	(0.00)	(0.66)	(0.93)	(0.89)
JAP-BR	0.3625	0.0950	-0.0670	0.0569	0.1992	-0.0103	-0.0217	-0.0151	0.1287	0.1236	-0.0986	-0.0091
	(0.00)	(0.23)	(0.01)	(0.03)	(0.00)	(0.50)	(0.61)	(0.47)	(0.13)	(0.09)	(0.00)	(0.72)
JAP-RUS	0.1540	0.1370	-0.0639	0.0133	0.1207	0.0068	-0.0254	0.0520	-0.0349	-0.1681	-0.0070	0.0097
	(0.03)	(0.00)	(0.00)	(0.57)	(0.00)	(0.75)	(0.56)	(0.02)	(0.44)	(0.01)	(0.49)	(0.49)
JAP-IND	0.1823	0.1512	-0.0233	-0.0088	0.0667	0.0477	0.0261	0.0074	-0.0801	0.2205	-0.0455	-0.0684
	(0.00)	(0.03)	(0.23)	(0.69)	(0.00)	(0.08)	(0.12)	(0.84)	(0.01)	(0.00)	(0.01)	(0.03)
JAP-CH	0.1821	-0.0235	-0.0133	0.0370	-0.0221	-0.0203	-0.0269	0.0283	-0.0355	-0.0995	-0.0171	0.0256
	(0.00)	(0.70)	(0.61)	(0.08)	(0.17)	(0.40)	(0.33)	(0.07)	(0.58)	(0.04)	(0.25)	(0.14)

C: Parameters in the BGARCH part

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Developed-Developed (D-D) combination											
US-UK	0.1483	0.1151	0.1040	0.2379	0.0702	-0.0066	0.3146	0.9678	-0.0237	0.0036	0.9418
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.88)	(0.00)	(0.00)	(0.04)	(0.76)	(0.00)
US-HO	0.1385	0.1159	0.1404	0.2055	0.0954	-0.0847	0.2903	0.9719	-0.0318	0.0256	0.9482
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	0.1238	0.0594	0.2956	0.2659	-0.0507	0.0238	0.2824	0.9608	0.0073	0.0073	0.9360
	(0.00)	(0.26)	(0.00)	(0.00)	(0.00)	(0.46)	(0.00)	(0.00)	(0.29)	(0.52)	(0.00)
UK-HO	0.1669	0.0543	0.1388	0.3531	-0.0250	0.0329	0.2116	0.9325	0.0031	0.0009	0.9704
	(0.00)	(0.03)	(0.00)	(0.00)	(0.15)	(0.07)	(0.00)	(0.00)	(0.58)	(0.90)	(0.00)
UK-JAP	0.1619	(0.11)	0.2713	(0.33)	-0.0219	-(0.05)	0.2786	(0.95)	-0.0107	(0.05)	0.9317
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.01)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)
HO-JAP	0.1447	(0.24)	(0.18)	(0.21)	0.0398	(0.01)	(0.29)	(0.99)	-0.0293	(0.02)	(0.93)
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.63)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
Emerging-Emerging (E-E) combination											
BR-RUS	0.3459	0.3623	0.0092	0.2294	0.0101	0.0736	0.2965	0.9592	-0.0038	-0.0357	0.9468
	(0.00)	(0.00)	(0.90)	(0.00)	(0.55)	(0.00)	(0.00)	(0.00)	(0.50)	(0.00)	(0.00)
BR-IND	0.3007	0.2330	0.3973	0.2333	-0.0073	0.0586	0.3398	0.9643	-0.0090	-0.0063	0.9017
	(0.00)	(0.00)	(0.00)	(0.00)	(0.74)	(0.00)	(0.00)	(0.00)	(0.32)	(0.39)	(0.00)
BR-CH	0.3688	-0.0173	0.1782	0.2528	-0.0655	-0.0152	0.2163	0.9484	0.0192	0.0048	0.9712
	(0.00)	(0.57)	(0.00)	(0.00)	(0.00)	(0.23)	(0.00)	(0.00)	(0.00)	(0.32)	(0.00)
RUS-IND	0.402	0.2204	0.1308	0.3654	-0.0147	0.0908	0.1975	0.9244	-0.0116	-0.0311	0.9692
	(0.00)	(0.00)	(0.00)	(0.00)	(0.60)	(0.00)	(0.00)	(0.00)	(0.30)	(0.00)	(0.00)
RUS-CH	0.3411	-0.0088	0.1612	0.3374	-0.0785	-0.0082	0.1932	0.9325	0.0172	0.0049	0.9764
	(0.00)	(0.74)	(0.00)	(0.00)	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)

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Table: 4.4 Continued from previous page

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	β_{11}	β_{12}	β_{21}	β_{22}
IND-CH	0.4529	0.0018	0.1695	0.3565	-0.0463	-0.0292	0.2156	0.9021	0.0211	0.0083	0.9714
	(0.00)	(0.95)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)
Developed-Emerging (D-E) combination											
US-BR	0.1450	0.2235	0.1110	0.2738	0.0014	0.0388	0.2010	0.9582	-0.0019	-0.0130	0.9739
	(0.00)	(0.00)	(0.00)	(0.00)	(0.91)	(0.21)	(0.00)	(0.00)	(0.60)	(0.11)	(0.00)
US-RUS	-0.1453	-0.1094	0.2696	0.2621	-0.0075	0.0068	0.3005	0.9595	0.0020	-0.0011	0.9479
	(0.00)	(0.02)	(0.00)	(0.00)	(0.41)	(0.76)	(0.00)	(0.00)	(0.50)	(0.89)	(0.00)
US-IND	-0.1520	-0.2415	0.3362	0.2698	-0.0041	0.0627	0.2942	0.9597	-0.0068	-0.0122	0.9261
	(0.00)	(0.00)	(0.00)	(0.00)	(0.75)	(0.01)	(0.00)	(0.00)	(0.23)	(0.13)	(0.00)
US-CH	-0.1564	-0.0206	0.1712	0.2726	-0.0026	-0.0083	0.2007	0.9554	0.0011	0.0010	0.9752
	(0.00)	(0.46)	(0.00)	(0.00)	(0.82)	(0.55)	(0.00)	(0.00)	(0.74)	(0.81)	(0.00)
UK-BR	0.1602	0.1866	0.1664	0.3446	-0.0203	0.1531	0.1709	0.9371	0.0010	-0.0414	0.9778
	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)
UK-RUS	0.1571	0.1984	0.1771	0.3104	0.0104	0.0704	0.2834	0.9444	-0.0027	-0.0307	0.9567
	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)	(0.00)	(0.00)	(0.19)	(0.00)	(0.00)
UK-IND	0.1571	0.0917	0.1180	0.3407	-0.0188	0.0926	0.1710	0.9358	0.0034	-0.0278	0.9832
	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)
UK-CH	0.1572	-0.0250	0.1643	0.3290	-0.0080	0.0110	0.1932	0.9382	0.0047	-0.0021	0.9768
	(0.00)	(0.43)	(0.00)	(0.00)	(0.41)	(0.50)	(0.00)	(0.00)	(0.12)	(0.71)	(0.00)
HO-BR	0.1625	0.2228	0.2308	0.2275	0.0305	-0.0234	0.2312	0.9707	-0.0121	0.0059	0.9598
	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.43)	(0.00)	(0.00)	(0.00)	(0.44)	(0.00)
HO-RUS	0.1603	0.2267	0.2475	0.2357	0.0220	0.0387	0.3107	0.9690	-0.0069	-0.0118	0.9423
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.25)	(0.00)	(0.00)	(0.09)	(0.25)	(0.00)
HO-IND	0.2296	0.2805	0.2146	0.3323	-0.0264	0.2217	0.2157	0.9402	0.0022	-0.0595	0.9421
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.74)	(0.00)	(0.00)
HO-CH	0.1497	0.0011	0.1732	0.2655	-0.0446	-0.0234	0.2165	0.9599	0.0117	0.0074	0.9707
	(0.00)	(0.98)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
JAP-BR	0.2580	0.0919	0.2552	0.2981	0.0019	0.0584	0.1940	0.9416	0.0026	-0.0228	0.9731
	(0.00)	(0.06)	(0.00)	(0.00)	(0.91)	(0.02)	(0.00)	(0.00)	(0.70)	(0.01)	(0.00)
JAP-RUS	0.2530	0.1476	0.3269	0.2601	0.0407	0.0130	0.3208	0.9550	-0.0163	0.0024	0.9366
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.55)	(0.00)	(0.00)	(0.00)	(0.84)	(0.00)
JAP-IND	0.2984	0.2300	0.1126	0.2745	0.0504	0.1083	0.2544	0.9422	-0.0088	-0.0502	0.9619
	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)
JAP-CH	0.3173	-0.0283	0.1770	0.3156	-0.0152	-0.0004	0.2102	0.9297	0.0092	0.0039	0.9721
	(0.00)	(0.37)	(0.00)	(0.00)	(0.28)	(0.98)	(0.00)	(0.00)	(0.05)	(0.50)	(0.00)

Note: $p-$values are given in parenthesis.

4.4.2.2 TVAR-BTGARCH-M model

Finally, we discuss, in detail, our proposed model i.e., the TVAR-BTGARCH-M model. This model incorporates asymmetry in the conditional variance model i.e., the asymmetric version of the BEKK model, as given in equation (4.4), as well as introduces two different market conditions *viz.*, up and down markets, as specified in equation (4.6). The choice of value of k is the same as stated in the TVAR-BGARCH-M model. i.e., $k = 20$. We first discuss about the estimates of the conditional mean part of the model. At the outset, it may be stated that for all the 3 pairs of combinations of countries, the mean spillover effects are positive whenever significant. In case of 6 pairs under D-D combination, the parameters signifying own dependences in terms of first lag coefficients of the two return series i.e., b_{11}^1, b_{11}^2, b_{22}^1, b_{22}^1, are significant in most of the cases. It may be noted that this numbers are a little higher than the corresponding numbers in the preceding model where variance was taken to be symmetric. As regards the mean spillovers across the two market movements, the relevant coefficients *viz.*, b_{21}^1, b_{12}^1, b_{21}^2, b_{12}^2, are significant in 6, 1, 5, 1 pairs, respectively. Thus it is seen that given the specification of the mean model in equation (4.5), the mean spillovers effects are responsive to the two market conditions for each of the pairs among the developed stock markets. In fact, there is no pair of developed stock markets where this spillover effect is insignificant in both directions. This observation is somewhat different from the corresponding one in the preceding model where this spillover effect was found to be insignificant in at least one market condition in a few pairs.

In case of all the 6 pairs of E-E combination of markets, the findings are similar with the exception that b_{12}^1 is now found to be insignificant for all combinations. The latter finding means that in down market the mean spillover effect does not exist in one direction. However, this does not mean that this effect is absent as a whole since the effect in the other direction as well as in the other market movement i.e., up market, are significant. In fact, as in D-D combination, there is no pair where there is no mean spillover in either direction or in either market condition.

The own lag dependence is significant in most of the 16 pairs in the D-E combination. Insofar as the mean spillover effects are concerned, the number of significant cases are 8,11, 11, 8, for b_{21}^1, b_{12}^1, b_{21}^2, b_{12}^2, respectively. Since the numbers are very close, it can be concluded that the prevalence of this effects are not much different from emerging to developed or *vice versa.*, or from up to down markets or *vice versa.*. As in the other two combinations, there are no cases where there are no spillover effects in either direction or in either market condition. Comparing these findings with those for TVAR-BGARCH-M model, we can conclude that introduction of asymmetry in H_t have led to better modelling considerations since for this model there is no pair of countries where mean spillover effect is absent.

Insofar as the spillover effects of the symmetric component of H_t are concerned, we find that this effect is present in all the 28 pairs of countries. In other words, one or more of the relevant coefficients *viz.*, α_{12}, α_{21}, β_{12}, β_{21}, are found to be significant in each of these 28 cases. Now, the more interesting and relevant observation in case of variance spillover is the spillover due to asymmetric component of H_t, which is to be studied in terms of significance of the parameters d_{12} and d_{21}. Specifically, we have found 26 pairs of countries - out of 28 - where either or both of d_{12} and d_{21} are significant. Thus there are only two pairs of countries where there is no spillover on account of asymmetric variance. Both these pairs of countries, US-India and Japan-Brazil, belong to D-E combination. Thus all the markets in D-D combination and E-E combination, and 14 pairs in D-E combination have asymmetric variance spillovers. Hence, there is practically no difference in this finding on asymmetric volatility spillovers insofar as the two groups of countries considered in this work, developed and emerging economies, are concerned. Finally, it is also noted that each of d_{11} and d_{22} which captures the asymmetry in the variance of respective own returns has been found to be significant for all the 28 pairs. The importance of the variance transmission channel, both symmetric and asymmetric, is thus found to be extremely important in this bivariate modelling framework for both the developed and emerging stock markets considered.

Finally, we come to the third and the last transmission channel for capturing spillover effects of one stock market to the other i.e., the BTGARCH-in-mean (BTGARCH-M. We begin by discussing the direct BTGARCH-in-mean effect as captured by λ_{13}^1, λ_{21}^1, λ_{13}^2 and λ_{21}^2, for each of the two market movements. In the D-D combination, the significant number of pairs for these four parameters are 0, 4, 3 and 4, respectively. This shows that the spillovers of risk of one market affecting the mean returns of the other market depend on the market condition *viz.*, whether the market is in down or up condition. Looking at these cases more carefully, we note that the pairs of countries where this effect of direct risk of one market on the mean returns of the other market, as understood in terms of the parameters λ_{13}^1 and λ_{13}^2 (from second country to first country), is present in the up market movement but not in the down market are : UK - Hong Kong, UK - Japan, and US - Hong Kong. As for the spillover effects of this nature as captured by λ_{21}^1 and λ_{21}^2, we note that the pairs where this effect (from the first country to second country) is significant in down market condition are UK-Hong Kong, UK - Japan, US - Hong Kong, US - Japan. The same in up market are UK-Japan, US-Hong Kong, US-Japan and US-UK. It may be noted that in the latter case, there are 3 pairs *viz.*, UK-Japan, US-Hong Kong, and US-Japan where this effect is significant in both the market situations. Combining all these, we find that out of the 6 pairs in D-D combination, there are 5 pairs where this spillover effect is found to be significant in at least one direction and in at least one market condition while in one case only *viz.*, Hong Kong-Japan where this effect is statistically insignificant in respect of both directions and both market movements. It is worthwhile to compare this final observation with those obtained in case of the VAR-BTGARCH-M model. In the latter model, we found 3 pairs where the spillover of direct risk of one market affecting the mean returns of the other market in at least one direction was found to be 3 while for the remaining 3 pairs there was no such effect in any of the two directions. It is then clear that introduction of market movements into the specification of the model, as done in our proposed model, has resulted in finding a better risk-return relationship since the number of pairs where this spillover is significant in at least one direction and one market condition has increased to 5 from 3, as noted earlier.

The findings on this spillover effect in the 6 pairs in E-E combination show that the incidence of this spillover effect is somewhat reduced as compared to the same in case of D-D combination. This is borne out by the fact that the number of pairs where the relevant parameters *viz.*, λ_{13}^1, λ_{21}^1, λ_{13}^2 and λ_{21}^2, are significant are 2, 1, 1, 1, respectively. This finding is not very unlikely since the flow of capital investment among the BRIC countries are yet to pick up as much as it is among the developed economies. Consequently, the interconnectedness among the markets and the existence of effective transmission channels are rather limited among these emerging economies. Comparing this finding with the one obtained for E-E combination in VAR-BTGARCH-M model, we note that in all there are only one pair of countries where this spillover was found to be significant in at least one direction; in the remaining 5 no such effect was found to be statistically significant. The usefulness of studying the risk-return relationship in the bivariate case by explicitly introducing the up and down market movements is thus established for this combination of countries as well since the number of pairs where this transmission channel is significant in at least one direction and at least one market condition is 3 for the proposed model, as opposed to 1 for the VAR-BTGARCH-M model.

Now, in the last combination of countries i.e., in the D-E combination, this spillover effect of direct risk of a developed market to the mean return of an emerging market is found to be significant in 13 pairs in all - 7 in down market and 6 in up market. The same figures from emerging to developed markets are 9 in all - 4 in down market and 5 in up market. Thus it can be noted that the incidence of this spillover effect is just a little more in the former as opposed to the latter. Hence, based on this finding, we can conclude that this BRIC group of economies has become important enough in influencing the stock markets of the developed countries. As in the other two combinations, in this D-E combination as well, the modelling improvement in terms of introduction of up and down markets is quite obvious. The number of pairs where this spillover effect was found to be significant at least in one direction in case of VAR-BTGARCH-M model where no consideration to market movements is made, is 9 while the same is 13 considering either direction and either market condition for the proposed TVAR-BTGARCH-M model. Finally, we note that there are 3 pairs *viz.*,US-India, US-China and Hong Kong - Japan, where no such spillover effect in any direction as well as in any market condition has been found. The same number in case of VAR-BTGARCH-M model is found to be 7. Thus, the usefulness of the proposed model is once again empirically established.

We conclude this section by discussing briefly the incidence of spillover effects of indirect risk (through the covariance term, h_{12t}) of one stock market on the mean returns of another market in both up and market movements. To this end, the parameters of interests are λ_{12}^1, λ_{12}^2, λ_{22}^1 and λ_{22}^2. Looking at the significance of each of these parameters, we note that λ_{12}^1, λ_{12}^{22}, λ_{21}^1 and λ_{22}^2 are significant in 1, 2, 4, 3 pairs, respectively for D-D combination, and 2, 5, 1, 4 pairs, respectively for E-E combination, and 4, 7, 8, 7 pairs, respectively for D-E combination of stock markets. Thus, it is found that up and down market conditions are relevant and important in bivariate set-up, as found for other spillover effects as well. This observation is further strengthened by noting that the corresponding numbers (combining the numbers in the two market conditions) in each of the 3 combination of countries have been found to be smaller in case of VAR-BTGARCH-M model.

Table 4.5: Estimates of the parameters of TVAR-BTGARCH-M model

A: Parameters in the conditional mean part of down market												
	VAR component in down market						BTGARCH-in-mean component in down market					
	a_1^1	a_2^1	b_{11}^1	b_{21}^1	b_{12}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
Developed-Developed (D-D) combination												
US-UK	0.0067	0.0086	-0.1695	0.3435	0.0013	-0.2791	0.1872	0.0362	-0.3129	-0.6132	0.0154	0.4580
	(0.87)	(0.84)	(0.00)	(0.00)	(0.97)	(0.00)	(0.13)	(0.76)	(0.17)	(0.02)	(0.85)	(0.00)
US-HO	0.0588	0.0273	-0.0801	0.4617	-0.0035	-0.1348	-0.0070	-0.0805	0.0333	0.2335	-0.0235	-0.0219
	(0.19)	(0.59)	(0.00)	(0.00)	(0.87)	(0.00)	(0.84)	(0.01)	(0.74)	(0.04)	(0.35)	(0.53)
US-JAP	0.0282	-0.0555	-0.1012	0.4991	0.0410	-0.0585	0.0305	-0.0779	-0.0428	0.2445	-0.0220	0.0043
	(0.37)	(0.24)	(0.00)	(0.00)	(0.06)	(0.02)	(0.20)	(0.00)	(0.51)	(0.00)	(0.28)	(0.89)
UK-HO	0.0552	0.0316	-0.0426	0.3341	-0.0279	-0.1727	0.0446	-0.0899	-0.0670	0.1456	0.0007	-0.0157
	(0.02)	(0.44)	(0.09)	(0.00)	(0.19)	(0.00)	(0.17)	(0.00)	(0.29)	(0.02)	(0.97)	(0.61)
UK-JAP	0.0506	-0.0090	-0.0409	0.3817	0.0128	-0.1424	-0.0338	-0.0879	0.0756	-0.0132	0.0014	0.0606
	(0.15)	(0.80)	(0.03)	(0.00)	(0.50)	(0.00)	(0.64)	(0.00)	(0.64)	(0.85)	(0.93)	(0.00)
HO-JAP	0.0257	0.0078	-0.0206	0.1049	-0.0032	-0.0787	0.1485	0.0073	-0.3501	-0.0667	0.0776	0.0257
	(0.78)	(0.92)	(0.35)	(0.00)	(0.88)	(0.00)	(0.23)	(0.95)	(0.21)	(0.79)	(0.32)	(0.71)
Emerging-Emerging (E-E) combination												
BR-RUS	-0.1285	0.2246	-0.0670	0.1353	0.0212	-0.0534	0.0687	-0.0405	-0.0576	-0.0049	-0.0084	0.0130
	(0.04)	(0.00)	(0.03)	(0.00)	(0.36)	(0.04)	(0.01)	(0.12)	(0.27)	(0.93)	(0.61)	(0.45)
BR-IND	0.0056	0.2467	-0.0917	0.0863	0.0062	-0.0249	0.0459	-0.0356	-0.0138	-0.0620	-0.0352	0.0177
	(0.94)	(0.00)	(0.00)	(0.00)	(0.85)	(0.41)	(0.05)	(0.15)	(0.83)	(0.38)	(0.09)	(0.51)
BR-CH	-0.1454	-0.1296	-0.0290	0.0627	-0.0194	-0.0169	0.0438	-0.0101	-0.3321	0.1396	0.0407	0.0263
	(0.13)	(0.08)	(0.27)	(0.00)	(0.57)	(0.34)	(0.09)	(0.41)	(0.16)	(0.00)	(0.19)	(0.20)
RUS-IND	0.2236	0.1001	0.0338	0.1020	-0.0060	-0.0448	0.0067	-0.0022	0.0236	-0.0340	-0.0361	0.0021
	(0.00)	(0.02)	(0.20)	(0.00)	(0.78)	(0.04)	(0.66)	(0.84)	(0.72)	(0.40)	(0.18)	(0.91)
RUS-CH	0.1048	-0.1561	0.0042	0.0460	-0.0004	-0.0191	0.0047	0.0063	-0.0534	-0.0451	-0.0008	0.0401
	(0.03)	(0.00)	(0.88)	(0.00)	(0.99)	(0.13)	(0.66)	(0.34)	(0.40)	(0.31)	(0.97)	(0.02)
IND-CH	0.1151	-0.1273	0.0069	0.0063	0.0033	-0.0042	-0.0453	0.0119	0.2779	-0.1704	-0.0186	0.0573
	(0.00)	(0.05)	(0.82)	(0.79)	(0.89)	(0.87)	(0.04)	(0.43)	(0.02)	(0.18)	(0.30)	(0.03)
Developed-Emerging (D-E) combination												
US-BR	0.0193	-0.0768	-0.0819	0.0165	-0.0313	-0.0321	0.0484	-0.0018	-0.0371	-0.0155	-0.0108	0.0264
	(0.64)	(0.25)	(0.00)	(0.47)	(0.06)	(0.17)	(0.41)	(0.98)	(0.65)	(0.89)	(0.63)	(0.45)
US-RUS	-0.0091	0.1738	-0.1050	0.2191	-0.0096	-0.0468	0.0693	-0.2548	-0.0875	0.4608	-0.0040	-0.0188
	(0.78)	(0.04)	(0.00)	(0.00)	(0.48)	(0.10)	(0.21)	(0.01)	(0.40)	(0.04)	(0.60)	(0.32)
US-IND	0.0563	0.1101	-0.1253	0.2554	-0.0379	-0.0193	0.0297	-0.0290	-0.0374	-0.0658	-0.0115	0.0133
	(0.17)	(0.19)	(0.00)	(0.00)	(0.05)	(0.41)	(0.26)	(0.46)	(0.62)	(0.62)	(0.34)	(0.62)
US-CH	-0.0190	-0.0634	-0.1012	0.1234	-0.0179	-0.0055	0.0051	-0.0144	0.2395	-0.5333	-0.0137	0.0503
	(0.76)	(0.41)	(0.00)	(0.00)	(0.36)	(0.79)	(0.79)	(0.55)	(0.42)	(0.22)	(0.43)	(0.07)
UK-BR	0.0722	-0.0290	-0.1304	0.0001	0.0891	-0.0662	0.0260	-0.0775	0.0253	0.0050	-0.0284	0.0488
	(0.14)	(0.59)	(0.00)	(1.00)	(0.00)	(0.02)	(0.72)	(0.58)	(0.79)	(0.98)	(0.12)	(0.05)
UK-RUS	0.0403	0.1290	-0.0285	0.0353	0.0010	-0.0110	0.0548	-0.0680	-0.0398	0.0575	-0.0019	-0.0064

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Table: 4.5 Continued from previous page

	a_1^1	a_2^1	b_{11}^1	b_{21}^1	b_{12}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
	(0.19)	(0.09)	(0.21)	(0.11)	(0.94)	(0.59)	(0.04)	(0.00)	(0.23)	(0.02)	(0.78)	(0.51)
UK-IND	0.0737	0.1074	-0.0632	0.1909	-0.0028	-0.0645	0.0190	-0.0904	0.0066	0.1610	-0.0138	-0.0260
	(0.00)	(0.07)	(0.00)	(0.00)	(0.85)	(0.00)	(0.22)	(0.00)	(0.75)	(0.00)	(0.03)	(0.15)
UK-CH	0.0240	-0.1336	-0.0497	0.0637	-0.0255	-0.0137	0.0374	0.0066	-0.2373	-0.2582	0.0092	0.0646
	(0.68)	(0.06)	(0.05)	(0.03)	(0.20)	(0.61)	(0.21)	(0.84)	(0.18)	(0.27)	(0.61)	(0.03)
HO-BR	0.0808	-0.1647	-0.1083	-0.0412	0.2208	-0.0436	-0.0447	0.0563	0.1012	-0.2869	-0.0100	0.0960
	(0.20)	(0.08)	(0.00)	(0.31)	(0.00)	(0.18)	(0.35)	(0.38)	(0.27)	(0.04)	(0.68)	(0.02)
HO-RUS	-0.0448	0.1417	-0.0834	0.0108	0.0940	-0.0022	0.0203	0.0218	-0.0281	-0.1130	0.0008	0.0196
	(0.43)	(0.14)	(0.01)	(0.79)	(0.00)	(0.94)	(0.52)	(0.69)	(0.67)	(0.37)	(0.94)	(0.36)
HO-IND	0.0881	0.0926	-0.0647	0.0537	0.0831	0.0049	-0.0130	-0.0526	0.0434	0.0197	-0.0166	0.0132
	(0.01)	(0.08)	(0.01)	(0.03)	(0.00)	(0.86)	(0.47)	(0.02)	(0.21)	(0.50)	(0.15)	(0.50)
HO-CH	0.0469	-0.1720	-0.0249	0.0043	-0.0258	0.0112	-0.0269	0.0377	0.0703	-0.2198	-0.0123	0.0957
	(0.44)	(0.01)	(0.14)	(0.82)	(0.18)	(0.50)	(0.30)	(0.12)	(0.36)	(0.01)	(0.56)	(0.00)
JAP-BR	0.1438	-0.1020	-0.0568	-0.0207	0.2484	-0.0295	0.0252	0.0393	0.2381	-0.1408	-0.1142	0.0388
	(0.06)	(0.14)	(0.05)	(0.61)	(0.00)	(0.35)	(0.49)	(0.37)	(0.00)	(0.03)	(0.00)	(0.15)
JAP-RUS	-0.0009	0.2196	-0.0489	-0.0032	0.1354	0.0146	0.0068	-0.0579	0.0321	0.1453	-0.0164	-0.0162
	(0.99)	(0.12)	(0.10)	(0.94)	(0.00)	(0.66)	(0.90)	(0.59)	(0.80)	(0.60)	(0.25)	(0.62)
JAP-IND	0.0465	0.1853	-0.0051	0.1333	0.1086	-0.0032	-0.0520	-0.1132	0.2133	0.2346	-0.0581	-0.0480
	(0.38)	(0.00)	(0.85)	(0.00)	(0.00)	(0.91)	(0.08)	(0.00)	(0.01)	(0.05)	(0.04)	(0.26)
JAP-CH	-0.1486	-0.2714	0.0380	-0.0257	-0.0699	-0.0069	0.0450	0.0722	-0.2766	-0.5078	0.0499	0.1234
	(0.12)	(0.01)	(0.16)	(0.31)	(0.01)	(0.75)	(0.22)	(0.11)	(0.10)	(0.02)	(0.12)	(0.00)

B: Parameters in the conditional mean part of up market

	VAR component in up market						BTGARCH-in-mean compnent in up market					
	a_1^2	a_2^1	b_{11}^2	b_{21}^2	b_{12}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
Developed-Developed (D-D) combination												
US-UK	0.0304	0.0590	-0.0419	0.2780	0.0055	-0.1995	-0.0795	-0.1570	0.1178	0.0247	0.0074	0.1169
	(0.33)	(0.04)	(0.12)	(0.00)	(0.81)	(0.00)	(0.46)	(0.06)	(0.48)	(0.89)	(0.93)	(0.31)
US-HO	0.0201	0.0088	-0.0587	0.4577	0.0263	-0.0574	-0.0262	-0.1132	0.1581	0.6107	-0.0322	-0.0305
	(0.57)	(0.87)	(0.03)	(0.00)	(0.14)	(0.01)	(0.32)	(0.10)	(0.01)	(0.00)	(0.15)	(0.56)
US-JAP	0.0194	0.1133	-0.0518	0.4835	0.0079	-0.0747	-0.0067	-0.1386	0.1871	0.3749	-0.0328	-0.0178
	(0.49)	(0.06)	(0.01)	(0.00)	(0.64)	(0.00)	(0.88)	(0.01)	(0.14)	(0.06)	(0.24)	(0.78)
UK-HO	0.0693	0.0265	-0.0578	0.3463	0.0134	-0.0584	-0.0095	-0.0560	0.0379	0.0279	-0.0508	0.0414
	(0.01)	(0.42)	(0.01)	(0.00)	(0.35)	(0.00)	(0.87)	(0.51)	(0.68)	(0.88)	(0.00)	(0.32)
UK-JAP	0.0598	0.0860	-0.0295	0.3964	-0.0128	-0.0985	-0.1262	-0.2643	0.2700	0.5140	-0.0413	-0.0158
	(0.00)	(0.04)	(0.12)	(0.00)	(0.36)	(0.00)	(0.15)	(0.00)	(0.18)	(0.00)	(0.01)	(0.75)
HO-JAP	0.0222	0.1227	0.0594	0.0174	-0.0602	-0.0015	-0.1142	-0.1074	0.2371	0.1700	-0.0050	-0.0253
	(0.76)	(0.07)	(0.00)	(0.48)	(0.00)	(0.96)	(0.19)	(0.09)	(0.24)	(0.24)	(0.94)	(0.67)
Emerging-Emerging (E-E) combination												
BR-RUS	0.0470	0.2495	-0.0005	0.2207	0.0091	-0.0488	-0.0065	-0.0351	0.0051	-0.1268	0.0081	0.0402
	(0.41)	(0.00)	(0.99)	(0.00)	(0.65)	(0.05)	(0.83)	(0.22)	(0.94)	(0.00)	(0.61)	(0.01)
BR-IND	-0.0081	0.1362	0.0078	0.1117	0.0401	0.0287	0.0281	-0.0065	0.1810	-0.2638	-0.0457	0.0962
	(0.91)	(0.00)	(0.75)	(0.00)	(0.06)	(0.14)	(0.48)	(0.80)	(0.01)	(0.03)	(0.05)	(0.01)
BR-CH	0.0511	0.1083	0.0197	0.0814	0.0180	-0.0259	0.0212	-0.0111	-0.1484	-0.1697	0.0121	0.0290
	(0.36)	(0.28)	(0.44)	(0.00)	(0.44)	(0.22)	(0.37)	(0.63)	(0.43)	(0.59)	(0.57)	(0.47)
RUS-IND	0.1193	0.0837	-0.0006	0.0226	0.0147	0.0508	0.0349	0.0376	-0.2089	-0.2590	0.0272	0.0694
	(0.09)	(0.06)	(0.98)	(0.21)	(0.60)	(0.05)	(0.13)	(0.03)	(0.00)	(0.00)	(0.45)	(0.07)
RUS-CH	0.2492	0.0318	0.0218	0.0474	-0.0251	-0.0221	0.0024	-0.0036	-0.1853	0.0149	-0.0219	0.0174
	(0.00)	(0.38)	(0.23)	(0.00)	(0.07)	(0.24)	(0.88)	(0.60)	(0.00)	(0.68)	(0.26)	(0.22)
IND-CH	0.1006	0.0008	0.0850	0.0373	-0.0127	-0.0309	-0.0371	0.0191	0.2869	-0.0704	-0.0140	0.0214
	(0.01)	(0.99)	(0.00)	(0.06)	(0.48)	(0.18)	(0.20)	(0.18)	(0.00)	(0.30)	(0.42)	(0.30)
Developed-Emerging (D-E) combination												
US-BR	0.1079	0.0251	-0.0396	0.0817	0.0090	-0.0410	-0.0333	-0.0498	0.0547	0.1135	-0.0413	-0.0063
	(0.03)	(0.69)	(0.12)	(0.02)	(0.55)	(0.11)	(0.67)	(0.67)	(0.60)	(0.48)	(0.01)	(0.83)
US-RUS	0.0466	0.1893	-0.0253	0.3102	-0.0079	-0.0571	-0.0334	-0.2314	0.0601	0.3052	-0.0100	-0.0027
	(0.24)	(0.00)	(0.35)	(0.00)	(0.50)	(0.03)	(0.52)	(0.05)	(0.34)	(0.19)	(0.18)	(0.90)
US-IND	0.0265	0.0505	-0.0524	0.2705	0.0107	0.0270	-0.0226	-0.0146	0.1933	-0.1022	-0.0211	0.0787
	(0.38)	(0.41)	(0.03)	(0.00)	(0.50)	(0.29)	(0.61)	(0.78)	(0.08)	(0.61)	(0.22)	(0.05)

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Table: 4.5 Continued from previous page

	a_1^2	a_2^1	b_{11}^2	b_{21}^2	b_{12}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
US-CH	0.0348	0.0153	-0.0417	0.1528	0.0180	-0.0241	0.0136	-0.0254	-0.0578	0.5338	-0.0103	0.0005
	(0.44)	(0.86)	(0.09)	(0.00)	(0.15)	(0.30)	(0.68)	(0.43)	(0.80)	(0.28)	(0.42)	(0.99)
UK-BR	0.1513	0.0227	-0.0811	0.0606	0.0754	-0.0315	0.0356	-0.2149	-0.0229	0.2481	-0.0567	0.0245
	(0.00)	(0.79)	(0.00)	(0.01)	(0.00)	(0.17)	(0.71)	(0.11)	(0.83)	(0.14)	(0.00)	(0.50)
UK-RUS	0.0677	0.2428	-0.0449	0.0031	0.0113	0.0029	-0.1390	-0.0129	0.1327	-0.2252	-0.0159	0.0347
	(0.00)	(0.00)	(0.02)	(0.92)	(0.20)	(0.89)	(0.00)	(0.81)	(0.01)	(0.05)	(0.03)	(0.07)
UK-IND	0.0899	0.0828	-0.0621	0.1194	0.0288	0.0622	-0.1231	-0.1009	0.2293	0.2896	-0.0430	0.0116
	(0.00)	(0.01)	(0.00)	(0.00)	(0.03)	(0.01)	(0.00)	(0.02)	(0.00)	(0.01)	(0.00)	(0.44)
UK-CH	0.0745	0.0368	-0.0400	0.1449	0.0100	-0.0312	-0.0241	0.0043	-0.2020	-0.0649	-0.0067	0.0192
	(0.07)	(0.65)	(0.12)	(0.00)	(0.37)	(0.30)	(0.49)	(0.90)	(0.16)	(0.84)	(0.53)	(0.56)
HO-BR	0.1235	-0.0215	-0.0420	0.0663	0.2232	-0.0218	0.0290	-0.0416	0.1445	-0.0125	-0.0821	0.0633
	(0.18)	(0.76)	(0.11)	(0.03)	(0.00)	(0.41)	(0.53)	(0.30)	(0.21)	(0.91)	(0.03)	(0.10)
HO-RUS	-0.0174	0.1693	-0.0033	-0.0020	0.0855	0.0039	0.0088	-0.0319	0.0810	-0.0111	-0.0061	0.0061
	(0.69)	(0.03)	(0.90)	(0.95)	(0.00)	(0.89)	(0.84)	(0.67)	(0.56)	(0.96)	(0.70)	(0.84)
HO-IND	0.0143	0.1599	-0.0236	0.0138	0.0631	0.0417	0.0227	0.1287	-0.0601	-0.2639	0.0105	-0.0128
	(0.62)	(0.00)	(0.38)	(0.62)	(0.00)	(0.12)	(0.58)	(0.02)	(0.56)	(0.05)	(0.68)	(0.82)
HO-CH	-0.0226	0.0413	0.0398	0.0297	0.0013	-0.0099	0.0873	-0.0115	-0.1381	0.0456	0.0057	0.0064
	(0.57)	(0.42)	(0.05)	(0.06)	(0.93)	(0.49)	(0.00)	(0.44)	(0.02)	(0.23)	(0.68)	(0.73)
JAP-BR	0.4745	0.1804	-0.0831	0.0623	0.2049	0.0110	-0.0988	-0.0243	0.4775	0.5592	-0.1495	-0.0951
	(0.00)	(0.24)	(0.00)	(0.04)	(0.00)	(0.69)	(0.10)	(0.46)	(0.00)	(0.00)	(0.00)	(0.17)
JAP-RUS	0.1696	0.2377	-0.0460	0.0171	0.1390	0.0211	-0.1458	-0.1217	0.3689	0.4399	-0.0385	-0.0544
	(0.10)	(0.04)	(0.10)	(0.60)	(0.00)	(0.45)	(0.10)	(0.20)	(0.07)	(0.11)	(0.06)	(0.09)
JAP-IND	0.1250	-0.0487	-0.0469	-0.0019	0.0624	0.0604	0.0053	0.1335	-0.1647	-0.3673	-0.0071	0.0746
	(0.14)	(0.44)	(0.12)	(0.94)	(0.01)	(0.04)	(0.94)	(0.02)	(0.26)	(0.01)	(0.85)	(0.12)
JAP-CH	0.2296	0.0222	-0.0002	0.0428	-0.0219	-0.0223	-0.0938	0.0044	0.2767	0.0079	-0.0400	0.0104
	(0.02)	(0.68)	(0.99)	(0.05)	(0.17)	(0.19)	(0.10)	(0.80)	(0.12)	(0.90)	(0.05)	(0.62)

C: Parameters in the BTGARCH part

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	d_{11}	d_{12}	d_{21}	d_{22}	β_{11}	β_{12}	β_{21}	β_{22}
Developed-Developed (D-D) combination															
US-UK	0.1878	0.0793	0.0922	-0.0149	0.1498	-0.1515	0.0776	0.4029	-0.0290	0.1572	0.2533	0.9003	0.0663	-0.0581	0.9866
	(0.00)	(0.00)	(0.00)	(0.76)	(0.00)	(0.00)	(0.03)	(0.00)	(0.52)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-HO	0.1476	0.0959	0.1615	0.1099	-0.0503	0.1835	-0.2386	0.3002	0.1135	-0.0727	0.2702	0.9599	-0.0266	0.0094	0.9444
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)
US-JAP	0.1553	0.0554	0.3131	-0.0150	0.0635	-0.1760	-0.1332	0.3755	0.0148	-0.0813	0.3387	0.9512	0.0015	0.0255	0.9159
	(0.00)	(0.17)	(0.00)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.53)	(0.02)	(0.00)	(0.00)	(0.86)	(0.00)	(0.00)
UK-HO	0.1376	0.0728	0.1861	-0.1017	0.0990	-0.1435	-0.0679	0.3669	0.0389	0.0201	0.2938	0.9416	0.0056	-0.0102	0.9591
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.07)	(0.53)	(0.00)	(0.00)	(0.39)	(0.26)	(0.00)
UK-JAP	0.1585	0.1117	0.2534	0.1278	-0.0418	-0.0318	-0.2370	0.4024	-0.0277	0.0662	0.2469	0.9513	-0.0110	0.0299	0.9224
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)	(0.00)	(0.37)	(0.06)	(0.00)	(0.00)	(0.19)	(0.00)	(0.00)
HO-JAP	0.1550	0.0974	0.2683	0.1954	-0.1336	0.1297	-0.2791	0.2979	0.0445	0.0558	0.2815	0.9757	-0.0349	0.0303	0.9118
	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.15)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Emerging-Emerging (E-E) combination															
BR-RUS	0.3673	0.3537	0.0966	-0.1229	0.0439	-0.0726	-0.2141	0.2883	0.0504	0.0483	0.2395	0.9460	0.0052	-0.0404	0.9517
	(0.00)	(0.00)	(0.10)	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)	(0.40)	(0.00)	(0.00)
BR-IND	0.3910	0.2691	0.3257	-0.0312	0.1062	-0.1945	-0.0195	0.3371	0.0197	0.0731	0.4725	0.9482	-0.0146	-0.0195	0.8831
	(0.00)	(0.00)	(0.00)	(0.47)	(0.00)	(0.00)	(0.71)	(0.00)	(0.60)	(0.01)	(0.00)	(0.00)	(0.28)	(0.22)	(0.00)
BR-CH	0.3461	0.0235	0.1911	0.0237	0.0252	0.0038	-0.2268	0.3422	-0.0341	0.0121	0.0913	0.9527	0.0153	-0.0043	0.9668

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Table: 4.5 Continued from previous page

	c_{11}	c_{12}	c_{13}	α_{11}	α_{12}	α_{21}	α_{22}	d_{11}	d_{12}	d_{21}	d_{22}	β_{11}	β_{12}	β_{21}	β_{22}
	(0.00)	(0.50)	(0.00)	(0.57)	(0.17)	(0.77)	(0.00)	(0.00)	(0.27)	(0.50)	(0.05)	(0.00)	(0.02)	(0.37)	(0.00)
RUS-IND	0.3920	0.3222	0.3010	-	0.1168	-	0.0533	0.3138	0.0891	0.1305	0.4342	0.9306	-	-	0.8990
				0.2892		0.0217							0.0533	0.0155	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.35)	(0.11)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)
RUS-CH	0.3428	0.0023	0.1814	-	0.1000	-	-	0.2878	-	-	0.1275	0.9356	0.0197	0.0013	0.9717
				0.2443		0.0086	0.1938		0.0093	0.0230					
	(0.00)	(0.92)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.71)	(0.05)	(0.00)	(0.00)	(0.00)	(0.66)	(0.00)
IND-CH	0.4327	-	0.2063	-	0.0729	-	-	0.5106	-	0.0735	-	0.8884	0.0486	-	0.9637
		0.0081		0.1446		0.0090	0.2495		0.0708		0.0881			0.0213	
	(0.00)	(0.79)	(0.00)	(0.00)	(0.00)	(0.51)	(0.00)	(0.00)	(0.03)	(0.00)	(0.08)	(0.00)	(0.00)	(0.01)	(0.00)
Developed-Emerging (D-E) combination															
US-BR	0.1391	0.2282	0.1090	-	-	0.1070	-	0.3272	0.0128	0.0993	0.1828	0.9654	-	-	0.9673
				0.0542	0.0017		0.1923						0.0032	0.0044	
	(0.00)	(0.00)	(0.00)	(0.06)	(0.90)	(0.00)	(0.00)	(0.00)	(0.40)	(0.03)	(0.00)	(0.00)	(0.37)	(0.57)	(0.00)
US-RUS	0.1538	0.0711	0.2680	-	0.0090	0.1198	-	0.3517	0.0228	0.0553	0.1254	0.9536	0.0027	0.0227	0.9370
				0.0344			0.3226								
	(0.00)	(0.06)	(0.00)	(0.12)	(0.37)	(0.00)	(0.00)	(0.00)	(0.02)	(0.11)	(0.00)	(0.00)	(0.39)	(0.01)	(0.00)
US-IND	0.1563	0.1726	0.4088	-	0.0511	-	-	0.3697	0.0044	0.0362	0.4436	0.9543	-	-	0.8814
				0.0260		0.2601	0.1114						0.0037	0.0014	
	(0.00)	(0.00)	(0.00)	(0.57)	(0.00)	(0.00)	(0.01)	(0.00)	(0.79)	(0.57)	(0.00)	(0.00)	(0.55)	(0.90)	(0.00)
US-CH	0.1445	0.0133	0.1904	0.0161	0.0037	0.0166	-	0.3734	0.0350	0.0316	-	0.9528	0.0081	-	0.9647
							0.2401				0.0712			0.0046	
	(0.00)	(0.71)	(0.00)	(0.52)	(0.74)	(0.36)	(0.00)	(0.00)	(0.02)	(0.15)	(0.19)	(0.00)	(0.02)	(0.29)	(0.00)
UK-BR	0.1294	0.1722	0.1818	-	0.0520	0.0611	-	0.3987	-	0.2001	0.1516	0.9467	0.0066	-	0.9719
				0.0505			0.1585		0.0101					0.0203	
	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)	(0.12)	(0.00)	(0.00)	(0.58)	(0.00)	(0.00)	(0.00)	(0.07)	(0.02)	(0.00)
UK-RUS	0.1563	0.2105	0.1906	-	-	0.1707	-	0.3837	0.0064	0.1264	0.2231	0.9548	-	-	0.9455
				0.0306	0.0246		0.2832						0.0058	0.0087	
	(0.00)	(0.00)	(0.00)	(0.13)	(0.01)	(0.00)	(0.00)	(0.00)	(0.52)	(0.00)	(0.00)	(0.00)	(0.02)	(0.18)	(0.00)
UK-IND	0.1388	0.1435	0.3977	-	0.0715	-	-	0.3663	0.0158	-	0.5326	0.9461	-	0.0276	0.8731
				0.1493		0.2404	0.1336			0.1995			0.0009		
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.33)	(0.00)	(0.00)	(0.00)	(0.87)	(0.01)	(0.00)
UK-CH	0.1299	-	0.1939	-	0.0268	-	-	0.3807	0.0276	0.0402	0.0603	0.9495	0.0112	-	0.9645
		0.0324		0.0482		0.0085	0.2387							0.0089	
	(0.00)	(0.36)	(0.00)	(0.06)	(0.01)	(0.61)	(0.00)	(0.00)	(0.13)	(0.09)	(0.15)	(0.00)	(0.00)	(0.08)	(0.00)
HO-BR	0.2028	0.2744	0.2883	0.1466	0.0722	-	0.0616	0.3114	-	0.1745	0.2597	0.9559	-	-	0.9457
						0.0634			0.0278				0.0148	0.0035	
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.14)	(0.23)	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.03)	(0.71)	(0.00)
HO-RUS	0.2318	0.1938	0.2928	0.0729	-	0.0668	-	0.3520	0.0120	0.1426	0.2098	0.9555	-	-	0.9313
					0.0292		0.3042						0.0035	0.0150	
	(0.00)	(0.00)	(0.00)	(0.03)	(0.09)	(0.04)	(0.00)	(0.00)	(0.50)	(0.00)	(0.00)	(0.00)	(0.62)	(0.10)	(0.00)
HO-IND	0.1930	0.2274	0.2716	-	-	0.2814	-	0.3646	-	0.2136	0.2719	0.9777	-	0.0337	0.8823
				0.0441	0.0711		0.2526		0.0231				0.0400		
	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HO-CH	0.1985	0.0116	0.1829	-	0.0299	-	-	0.3562	-	0.0172	0.1173	0.9518	0.0160	-	0.9691
				0.1280		0.0003	0.2091		0.0775					0.0019	
	(0.00)	(0.71)	(0.00)	(0.00)	(0.02)	(0.98)	(0.00)	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.00)	(0.65)	(0.00)
JAP-BR	0.2522	-	0.3710	-	0.1156	-	-	0.3508	0.0305	0.0052	0.3141	0.9321	0.0166	-	0.9492
		0.0355		0.1096		0.1195	0.0911							0.0217	
	(0.00)	(0.53)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.87)	(0.00)	(0.00)	(0.05)	(0.02)	(0.00)
JAP-RUS	0.2953	0.0574	0.3180	0.0534	0.0032	0.1000	-	0.3700	0.0288	0.1284	0.1520	0.9349	0.0135	-	0.9363
							0.3243							0.0260	
	(0.00)	(0.26)	(0.00)	(0.07)	(0.82)	(0.00)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)	(0.02)	(0.01)	(0.00)
JAP-IND	0.2359	-	0.4243	0.0693	0.0779	-	0.0615	0.3283	0.0695	0.0735	0.4939	0.9594	-	0.0597	0.8521
		0.0027				0.2613							0.0335		
	(0.00)	(0.96)	(0.00)	(0.03)	(0.01)	(0.00)	(0.18)	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JAP-CH	0.3237	-	0.1878	0.0133	0.0231	0.0177	-	0.4310	-	0.0557	0.1299	0.9304	0.0197	-	0.9654
		0.0308					0.2242		0.0464					0.0111	
	(0.00)	(0.31)	(0.00)	(0.75)	(0.15)	(0.25)	(0.00)	(0.00)	(0.07)	(0.01)	(0.00)	(0.00)	(0.00)	(0.08)	(0.00)

Note: $p-$values are given in parenthesis.

4.5 Findings on Tests of Hypotheses

Based on our empirical findings so far, we can state that consideration to stock market movements like up and down markets in specifying the conditional mean model along with asymmetry in the conditional variance are very important in proper modelling of the risk-return relationship in bivariate set-up. Thus, the effectiveness of the proposed TVAR-BTGARCH-M model, which explicitly incorporates these two aspects, have been empirically established. It may be recalled that the other four models - the VAR-BGARCH, VAR-BGARCH-M, VAR-BTGARCH-M, TVAR-BGARCH-M - can be obtained by putting restrictions on the parameters of the proposed model. In this section, we first report results of the LR test carried out to find if our proposed model is statistically a better model in comparison to these restricted models. We also discuss the results of the Wald test of different hypotheses of interests mentioned in Section 4.3 of this chapter.

4.5.1 Results of the LR test

At the very outset we note from the maximized log-likelihood values of the five models, given in the last rows of Tables 4.1 through 4.5, that this value is maximum for the proposed model for each of the 28 pairs of countries. Since these models are nested parametrically, we can find if the difference in the maximized log-likelihood values of the proposed model and any of the other four models, is statistically significant. To that end, the values of the LR test statistic are given in Table 4.6.

We note from this table that except for the VAR-BTGARCH-M model, each of the null hypotheses representing the VAR-BGARCH, VAR-BGARCH-M and TVAR-BGARCH-M models is rejected in favour of the alternative hypothesis representing the proposed TVAR-BTGARCH-M model. And this is so for each of the 28 pairs covering all the 3 combinations of stock markets *viz.*, D-D, E-E, and D-E combinations. Hence, our model performs uniformly better than each of these 3 models. This establishes the statistical relevance and importance of asymmetry in variance and market conditions characterised as up and down in studying the risk-return relationship in bivariate set-up. The findings in respect of VAR-BTGARCH-M is that although the maximum likelihood value is higher in case of TVAR-BTGARCH-M model for each of the 28 pairs, the difference is not always statistically significant. It is likely that such findings would depend on the pairs of countries concerned. In fact, looking at the LR test statistic values in column 4 of Table 4.6, we note that there are only 9 pairs of countries in all where the proposed model is significantly better than VAR-BTGARCH-M model. Out of these 9 pairs, 4 are in D-D combination *viz.*, US-UK, US-Hong Kong, UK-Hong Kong and Hong Kong - Japan, and 5 in D-E combinations, *viz.*, UK-India, Hong Kong-China, Japan-Brazil, Japan-India and Japan-China. For the remaining 19 pairs, these two models can be considered to be statistically the same. If we look into the test statistic values of these 19 pairs, it is important to note that the 2 pairs in case of D-D combination are US-Japan and UK-Japan. This means that up and down market movements are not very relevant insofar as the stock market of Japan and the stock market of US/UK are concerned. On the other hand in case of D-E combination, these market conditions are very relevant in all pairs where Japan is a member except for Japan-Russia pair.

In case of E-E combination, there is not a single pair for which the proposed model is significantly better than VAR-BTGARCH-M model although, as already stated, the maximised log-likelihood value for the proposed model is higher than that for this model for each of these pairs. This is consistent with the finding in the preceding section where it was observed that the coefficient capturing mean spillovers in one or more of up and down markets were found to be insignificant in most of the cases in E-E combination. In fact, this is also similar for D-E combination where these two models were found to be statistically the same. However, as we would note in the following section that this finding does not necessarily mean that none of the spillover effects concerning up and down market conditions is statistically significant. The statistical insignificance of the LR test statistic values concerning these two models, wherever applicable, essentially suggests that overall the two models perform equally well[7]. But, in terms of testing with one or more parameters concerning one or both the features associated with the proposed model, it has been found, as revealed in the next section, that the relevant null hypotheses are statistically significant.

Table 4.6: LR test statistic values for testing the restricted models against the proposed TVAR-BTGARCH-M model

Pair of Countries \ Restricted Models	VAR-BGARCH	VAR-BGARCH-M	VAR-BTGARCH-M	TVAR-BGARCH-M
Developed-Developed (D-D) combination				
US-UK	310.4107	276.6926	29.9180	266.3696
	(0.00)	(0.00)	(0.00)	(0.00)
US-HO	236.5469	231.6009	22.0453	222.4398
	(0.00)	(0.00)	(0.04)	(0.00)
US-JAP	271.3023	258.6502	11.0765	248.3509

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[7]It may be noted, in this context, that introduction of the two market conditions entails a total of 12 additional parameters and consequently degrees of freedom of the χ^2 distribution is 12 under the null hypothesis.

Table: 4.6 Continued from previous page

Restricted model / Pair of markets	VAR-BGARCH	VAR-BGARCH-M	VAR-BTGARCH-M	TVAR-BGARCH-M
	(0.00)	(0.00)	(0.52)	(0.00)
UK-HO	265.3708	255.8212	21.7922	235.3920
	(0.00)	(0.00)	(0.04)	(0.00)
UK-JAP	300.6411	278.8744	10.7668	258.2803
	(0.00)	(0.00)	(0.55)	(0.00)
HO-JAP	179.2204	171.9553	23.1999	144.7494
	(0.00)	(0.00)	(0.03)	(0.00)
Emerging-Emerging (E-E) combination				
BR-RUS	118.7243	114.4347	5.5448	104.4714
	(0.00)	(0.00)	(0.94)	(0.00)
BR-IND	167.0069	157.9839	14.7120	149.6816
	(0.00)	(0.00)	(0.26)	(0.00)
BR-CH	123.1087	117.8625	10.5337	110.2682
	(0.00)	(0.00)	(0.57)	(0.00)
RUS-IND	189.6869	162.1741	17.5777	144.5543
	(0.00)	(0.00)	(0.13)	(0.00)
RUS-CH	48.9659	41.1539	3.1671	32.0956
	(0.00)	(0.00)	(0.99)	(0.00)
IND-CH	144.7957	136.8135	9.3279	122.8175
	(0.00)	(0.00)	(0.67)	(0.00)
Developed-Emerging (D-D) combination				
US-BR	158.8874	150.8852	17.9935	133.3312
	(0.00)	(0.00)	(0.12)	(0.00)
US-RUS				
US-IND	256.9747	253.0879	14.1108	240.1067
	(0.00)	(0.00)	(0.29)	(0.00)
US-CH	228.4155	218.7520	12.7065	206.7543
	(0.00)	(0.00)	(0.39)	(0.00)
UK-BR	220.2400	209.2954	13.4949	185.5338
	(0.00)	(0.00)	(0.33)	(0.00)
UK-RUS	202.6087	193.1067	16.7866	174.4913
	(0.00)	(0.00)	(0.16)	(0.00)
UK-IND	316.3215	305.2228	30.9916	285.0722
	(0.00)	(0.00)	(0.00)	(0.00)
UK-CH	201.3465	192.0526	12.2433	172.5383
	(0.00)	(0.00)	(0.43)	(0.00)
HO-BR	165.1730	159.5621	13.6182	149.4750
	(0.00)	(0.00)	(0.33)	(0.00)
HO-RUS	163.2420	157.2064	7.6707	150.6169
	(0.00)	(0.00)	(0.81)	(0.00)
HO-IND	247.4907	240.5331	13.2264	223.4806
	(0.00)	(0.00)	(0.35)	(0.00)
HO-CH	105.3775	99.3229	18.5527	79.9706

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Restricted model / Pair of markets	VAR-BGARCH	VAR-BGARCH-M	VAR-BTGARCH-M	TVAR-BGARCH-M
	(0.00)	(0.00)	(0.10)	(0.00)
JAP-BR	192.9363	179.0263	22.7412	163.1982
	(0.00)	(0.00)	(0.03)	(0.00)
JAP-RUS	177.3108	169.4717	4.9774	163.1354
	(0.00)	(0.00)	(0.96)	(0.00)
JAP-IND	273.0070	272.3437	37.2518	216.7847
	(0.00)	(0.00)	(0.00)	(0.00)
JAP-CH	137.0727	124.8511	18.9639	113.3582
	(0.00)	(0.00)	(0.09)	(0.00)

Note: $p-$values are given in parenthesis.

4.5.2 Results of the Wald test

We now discuss the results of the Wald test carried out for testing different null hypotheses which specify the complete absence of each of the 3 types of spillovers or transmission channels for each of up and down markets, wherever relevant. We also present the findings on the null hypothesis of equality of spillover effects in the two market movements considered. These results are presented in Tables 4.7 through 4.9.

Tests of spillovers in mean

The first null hypothesis tested in this case is, as stated in Section 4.3.2, H^a_{01}: $b^1_{12} = b^2_{12} = 0$, and the alternative hypothesis H^a_{11}: either or both of $b^1_{12} \neq 0$, $b^2_{12} \neq 0$. Looking at Table 4.7, we find that except for Hong Kong - Japan in D-D combination and Brazil - China in E-E combination and 9 pairs in D-E combination, the null hypothesis of 'no spillovers in mean from the second market to the first market in both up and down market movements' cannot be rejected. It is thus noted that the mean spillovers from second country to first country for all but the 2 pairs mentioned above in the D-D and E-E combinations, are absent. Looking at these countries, we find that UK, Hong Kong, Japan have no spillover on US stock markets and Hong Kong and Japan have no such effects on the UK stock market in both up and down market conditions. Similarly, in E-E combination, Russia and India have no effect on Brazil's stock market; so is the case of China on Russia and India, and India on Russia. In case of D-E combination, we find that mean spillovers from some of the emerging countries to developed countries are present and the number of such pairs is nine. These pairs are: UK-Brazil, UK-India, Hong Kong-Brazil, Hong Kong-Russia, Hong Kong-India, Japan-Brazil, Japan-Russia, Japan-India and Japan-China.

We now consider the null hypothesis of 'no spillover in mean from the first market to the second market in both up and down market movements' i.e., H^b_{01}: $b^1_{21} = b^2_{21} = 0$. Here we note that in all the

6 cases in D-D combination, 5 cases in E-E combination, and 12 cases in D-E combination where the mean spillover effects in this(from first to second) direction are significant in one or both of the up and down markets. Combining these spillovers in the direction from first to second and the mean spillovers from second to first, we can conclude that except for one pair in the E-E combination (India-China) and two cases in D-E combination (US-Brazil and Hong Kong-China), the mean spillovers is present in at least one direction and in one market condition. These findings are the same as obtained in the preceding section where significance of each coefficient was tested separately.

Regarding testing of hypothesis on equality of spillovers in the two markets - from second to first market - we have only 2 pairs (UK-Hong Kong and Hong Kong - Japan), in D-D combination, 1 pair (Brazil-China) in E-E combination and 3 pairs (US-Brazil, US-India and UK-China) in D-E combination where the mean spillover effects is different in the up and down markets. On the other hand, for the same spillover effect from first to second market, the corresponding null hypothesis i.e., H_{02}^b: $b_{21}^1 = b_{21}^2$ is rejected in 2 pairs (US-UK and Hong Kong- Japan) in D-D combination, 2 pairs (Brazil-Russia and Russia-India) in E-E combination and 8 pairs (US-Russia, UK-Russia, UK-India, UK-China, Hong Kong- Brazil, Japan -Brazil, Japan-India and Japan - China) in D-E combination. If we combine these 2 findings on mean spillover effects being different in the 2 market conditions, the total number is 16 of which two pairs (Hong Kong-Japan and UK-China) are in both directions. Of these 16 cases, 3 each are in D-D and E-E combinations and the remaining 10 in D-E combination of markets. Thus, we may finally conclude that the incidence of up and down market conditions having significantly different mean spillover effects is quite large being 16 out of 28 pairs of stock markets considered in this study.

Table 4.7: Wald test statistic values for absence as well as equality of mean spillovers

Hypothesis	$b_{21}^1 = b_{21}^2 = 0$	$b_{12}^1 = b_{12}^2 = 0$	$b_{21}^1 = b_{21}^2$	$b_{12}^1 = b_{12}^2$
Developed-Developed (D-D) combination				
US-UK	0.0543	230.2604	0.0116	3.8146
	(0.97)	(0.00)	(0.91)	(0.05)
US-HO	2.1644	519.0995	1.0811	0.0135
	(0.34)	(0.00)	(0.30)	(0.91)
US-JAP	3.9348	554.0898	1.6785	0.1688
	(0.14)	(0.00)	(0.20)	(0.68)
UK-HO	2.9995	287.4422	2.9896	0.1095

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Hypothesis	$b^1_{21} = b^2_{21} = 0$	$b^1_{12} = b^2_{12} = 0$	$b^1_{21} = b^2_{21}$	$b^1_{12} = b^2_{12}$
	(0.22)	(0.00)	(0.08)	(0.74)
UK-JAP	1.0875	341.3354	1.0772	0.2330
	(0.58)	(0.00)	(0.30)	(0.63)
HO-JAP	8.4949	17.1490	4.0541	6.3349
	(0.01)	(0.00)	(0.04)	(0.01)
Emerging-Emerging (E-E) combination				
BR-RUS	1.0564	89.7355	0.1602	5.4602
	(0.59)	(0.00)	(0.69)	(0.02)
BR-IND	2.4787	39.9374	0.7786	0.6733
	(0.29)	(0.00)	(0.38)	(0.41)
BR-CH	4.8188	96.7337	3.3860	1.3350
	(0.09)	(0.00)	(0.07)	(0.25)
RUS-IND	0.2195	15.0535	0.1624	6.0840
	(0.90)	(0.00)	(0.69)	(0.01)
RUS-CH	2.0262	14.9593	0.4230	0.0032
	(0.36)	(0.00)	(0.52)	(0.95)
IND-CH	0.5205	3.5617	0.2947	1.1161
	(0.77)	(0.17)	(0.59)	(0.29)
Developed-Emerging (D-D) combination				
US-BR	3.5262	3.6276	3.2403	2.0840
	(0.17)	(0.16)	(0.07)	(0.15)
US-RUS	1.4537	1365.4727	0.0137	39.1971
	(0.48)	(0.00)	(0.91)	(0.00)
US-IND	4.1051	93.6009	3.5555	0.0872
	(0.13)	(0.00)	(0.06)	(0.77)
US-CH	2.6638	41.1206	2.1668	0.4546
	(0.26)	(0.00)	(0.14)	(0.50)
UK-BR	59.0778	6.7938	0.4603	1.9510

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Hypothesis	$b_{21}^1 = b_{21}^2 = 0$	$b_{12}^1 = b_{12}^2 = 0$	$b_{21}^1 = b_{21}^2$	$b_{12}^1 = b_{12}^2$
	(0.00)	(0.03)	(0.50)	(0.16)
UK-RUS	1.3317	11.1641	0.4983	4.5721
	(0.51)	(0.00)	(0.48)	(0.03)
UK-IND	4.8167	145.7678	2.3352	4.6039
	(0.09)	(0.00)	(0.13)	(0.03)
UK-CH	3.7248	28.8344	3.6339	5.3240
	(0.16)	(0.00)	(0.06)	(0.02)
HO-BR	212.6024	5.6925	0.0071	4.6829
	(0.00)	(0.06)	(0.93)	(0.03)
HO-RUS	44.6095	0.0699	0.1118	0.0580
	(0.00)	(0.97)	(0.74)	(0.81)
HO-IND	31.3275	5.9865	0.5194	1.0436
	(0.00)	(0.05)	(0.47)	(0.31)
HO-CH	2.2437	2.8635	1.3397	1.1025
	(0.33)	(0.24)	(0.25)	(0.29)
JAP-BR	252.8898	5.4243	2.5319	3.1775
	(0.00)	(0.07)	(0.11)	(0.07)
JAP-RUS	120.3642	0.2866	0.0199	0.1532
	(0.00)	(0.87)	(0.89)	(0.70)
JAP-IND	27.6880	17.9564	2.1810	12.1314
	(0.00)	(0.00)	(0.14)	(0.00)
JAP-CH	8.7105	4.7872	2.5754	4.1829
	(0.01)	(0.09)	(0.11)	(0.04)

Note: $p-$values are given in parenthesis.

Tests of spillovers in conditional variance

To start with, we recall that the results of tests on spillovers in the asymmetric component of conditional variance from first stock market to second stock market as well as from second to first were reported in the preceding section. There we found that in 26 pairs of countries, the variance spillovers due to asymmetric component were found to be significant in at least one direction. Now, we begin with testing for joint spillovers in this case i.e., the null hypothesis H_{03}: $d_{12} = d_{21} = 0$ against the alternative H_{13}: at least one of d_{12} and d_{21} is different from zero. The results of this test, which are presented in Table 4.8, show that the null hypothesis on this spillover effect cannot be rejected in 1 pair (UK-Japan) in D-D combination, 2 pairs (Brazil-China and Russia-China) in E-E combination and 1 pair (US-India) in D-E combination. In all other cases, the null hypothesis is found to be rejected.

We now discuss about the tests for detecting spillovers in the symmetric component of the conditional variance from one market to another. First we report the results concerning spillover from second market to first market i.e., the null hypothesis here is H_{04}^{a}: $\alpha_{12} = \beta_{12} = 0$. From column 5 of Table 4.8, we find that in all but two pairs, this null hypothesis is rejected. The two pairs where the null hypothesis could not be rejected belong to D-E combination and these are US-Brazil and US-Russia. As regards the other null hypothesis *viz.*, 'no spillovers in the symmetric component of variance from first market to second' which is specified as H_{04}^{b}: $\alpha_{21} = \beta_{21} = 0$, we find that there are 3 pairs (Brazil China, Russia-India, and Russia-China)in E-E combination and 5 pairs (US-China, UK-China, Hong Kong - Brazil, Hong Kong - China and Japan - China) in D-E combination where this null hypothesis could not be rejected. That the number of pairs where the spillover from first to second market is absent is somewhat higher than the corresponding number in the reverse direction can be explained by the fact that it is only expected that some emerging economies are likely not to influence some other emerging or developed stock markets. On the whole, we note that the spillover effects in the symmetric component of variance of stock returns of one stock market to another are predominantly present irrespective of the status of the two stock markets concerned.

Table 4.8: Wald test statistic values for absence as well as equality of volatility spillovers

Hypothesis	$d_{12} = d_{21} = 0$	$d_{12} = 0$	$d_{21} = 0$	$\alpha_{12} = \beta_{12} = \alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$
Developed-Developed (D-D) combination						
US-UK	18.2305	0.41976	12.0345	78.74059	26.9164	62.1071
	(0.00)	(0.52)	(0.00)	(0.00)	(0.00)	(0.00)
US-HO	48.3816	37.5594	10.6419	68.51671	25.6505	61.0484
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	5.87999	0.40009	5.68545	68.45352	9.35174	52.5485

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Table 4.8 Continued from previous page

Hypothesis	$d_{12} = d_{21} = 0$	$d_{12} = 0$	$d_{21} = 0$	$\alpha_{12} = \beta_{12} = \alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$
	(0.05)	(0.53)	(0.02)	(0.00)	(0.01)	(0.00)
UK-HO	6.06457	3.37424	0.39815	38.33697	20.9728	31.8741
	(0.05)	(0.07)	(0.53)	(0.00)	(0.00)	(0.00)
UK-JAP	3.88195	0.80667	3.68241	24.52927	10.3836	10.9175
	(0.14)	(0.37)	(0.05)	(0.00)	(0.01)	(0.00)
HO-JAP	9.76705	2.06716	2.94589	83.68873	36.6245	67.5504
	(0.01)	(0.15)	(0.09)	(0.00)	(0.00)	(0.00)
Emerging-Emerging (E-E) combination						
BR-RUS	12.1013	7.6408	3.1883	21.9011	5.1709	21.2209
	(0.00)	(0.01)	(0.07)	(0.00)	(0.08)	(0.00)
BR-IND	10.3840	0.2798	7.2307	129.5484	26.8355	115.0289
	(0.01)	(0.60)	(0.01)	(0.00)	(0.00)	(0.00)
BR-CH	1.4870	1.2066	0.4449	6.5792	6.0852	0.8751
	(0.48)	(0.27)	(0.50)	(0.16)	(0.05)	(0.65)
RUS-IND	43.6511	6.7304	36.5263	43.5204	37.6766	3.6939
	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.16)
RUS-CH	4.3116	0.1417	3.9343	37.0977	33.6671	2.8257
	(0.12)	(0.71)	(0.05)	(0.00)	(0.00)	(0.24)
IND-CH	14.6859	4.8053	10.6817	37.9090	37.4420	7.8059
	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.02)
Developed-Emerging (D-D) combination						
US-BR	8.0265	0.6941	4.5351	21.1952	1.3411	15.9686
	(0.02)	(0.40)	(0.03)	(0.00)	(0.51)	(0.00)
US-RUS	7.9768	5.1698	2.5020	21.8091	0.8917	16.6161
	(0.02)	(0.02)	(0.11)	(0.00)	(0.64)	(0.00)
US-IND	0.4891	0.0725	0.3230	56.6595	10.8862	55.3370

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Table 4.8 Continued from previous page

Hypothesis	$d_{12} = d_{21} = 0$	$d_{12} = 0$	$d_{21} = 0$	$\alpha_{12} = \beta_{12} = \alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$
	(0.78)	(0.79)	(0.57)	(0.00)	(0.00)	(0.00)
US-CH	8.6432	5.1745	2.0680	10.5165	7.8426	1.6942
	(0.01)	(0.02)	(0.15)	(0.03)	(0.02)	(0.43)
UK-BR	24.4531	0.3111	24.3537	30.4756	19.4168	12.7599
	(0.00)	(0.58)	(0.00)	(0.00)	(0.00)	(0.00)
UK-RUS	18.1076	0.4108	16.3685	37.7775	7.7477	35.8114
	(0.00)	(0.52)	(0.00)	(0.00)	(0.02)	(0.00)
UK-IND	32.1476	0.9584	29.7502	134.0169	52.2032	100.6156
	(0.00)	(0.33)	(0.00)	(0.00)	(0.00)	(0.00)
UK-CH	5.0727	2.2705	2.7949	14.0747	11.9787	3.2038
	(0.08)	(0.13)	(0.09)	(0.01)	(0.00)	(0.20)
HO-BR	20.3428	1.0410	20.0656	18.4560	16.0557	4.0145
	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.13)
HO-RUS	20.8295	0.4568	18.0280	9.2830	4.6456	6.4938
	(0.00)	(0.50)	(0.00)	(0.05)	(0.10)	(0.04)
HO-IND	57.5154	1.1060	55.5055	195.8099	33.6550	157.8743
	(0.00)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)
HO-CH	13.3806	13.1171	0.6851	16.9782	16.8322	0.2326
	(0.00)	(0.00)	(0.41)	(0.00)	(0.00)	(0.89)
JAP-BR	3.0283	2.8922	0.0285	71.6099	60.5573	14.3939
	(0.22)	(0.09)	(0.87)	(0.00)	(0.00)	(0.00)
JAP-RUS	13.6694	2.7661	11.5661	21.1917	9.9115	14.0662
	(0.00)	(0.10)	(0.00)	(0.00)	(0.01)	(0.00)
JAP-IND	12.8199	7.3546	3.5747	81.1058	19.3076	79.0561
	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.00)
JAP-CH	10.2586	3.3708	6.6759	22.7884	19.5505	4.1543

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Table 4.8 Continued from previous page

Hypothesis	$d_{12} = d_{21} = 0$	$d_{12} = 0$	$d_{21} = 0$	$\alpha_{12} = \beta_{12} = \alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$	$\alpha_{12} = \beta_{12} = 0$
	(0.01)	(0.07)	(0.01)	(0.00)	(0.00)	(0.13)

Note: $p-$values are given in parenthesis.

Tests of no BTGARCH-in-mean effect from one stock market to another

The first null hypothesis of interest in testing for this spillover effect is H_{06}^{a}: $\lambda_{13}^{1} = \lambda_{13}^{2} = 0$, i.e., no spillovers of direct risk of second market to the mean returns of first market in both up and down market movements. From Table 4.9 we find that there are in all 11 pairs where this hypothesis is rejected. The pairs are UK-Hong Kong and UK-Japan in D-D combination, Brazil-India in E-E combination and US-Brazil, UK-Brazil, UK-Russia, UK-India, Hong Kong-Brazil, Japan-Brazil, Japan-Russia and Japan-China. The incidence of no spillover effect of risk from first market to the mean return of second market in both up and down market movements is specified by the null hypothesis H_{06}^{b}: $\lambda_{21}^{1} = \lambda_{21}^{2} = 0$. This hypothesis is found to be rejected in 4 pairs in D-D combination and 1 pair in the E-E combination and 5 pairs in D-E combination. Combining these 2 findings, we find that there are 11 pairs of stock returns where this BTGARCH-in-mean spillover is altogether absent i.e., where risk of either stock market does not directly affect the mean return of the other market in both market conditions. These pairs are US-UK, and Hong Kong-Japan in D-D combination, Brazil-Russia, Brazil-China, Russia-China and India-China in E-E combination, and US-India, US-China, UK-China, Hong Kong-Russia and Hong Kong-India in D-E combination. Thus, we can conclude that the proposed TVAR-BTGARCH-M model which, *inter alia* , has an 'in-mean' component so as to incorporate the effect of risk directly on the conditional mean return, is found to be useful since in the remaining 17 pairs this effect is found to be significant.

Given the specification of the model, this spillover effect can also be studied in terms of indirect risk. The relevant parameters in the context of the model on returns on the first market are λ_{12}^{1} and λ_{12}^{2}, and λ_{22}^{1} and λ_{22}^{2} for the second market. The corresponding null hypotheses H_{06}^{c}: $\lambda_{12}^{1} = \lambda_{12}^{2} = 0$ and H_{06}^{d}: $\lambda_{22}^{1} = \lambda_{22}^{2} = 0$ are found to be rejected, from Table 4.9, in 13 and 17 pairs of stock returns, respectively. It is also worth noting that all the 8 pairs of countries where neither of the indirect spillover effect is found to be significant belong to the D-E combination. Thus, it indicates that while all pairs under D-D and E-E combinations have indirect spillover effects, the same in case of D-E combination is in case of only half of the 16 pairs.

We now come to the last of the tests done in this chapter *viz.*, test of equality of each of the parameters of BTGARCH-in-mean effects in up and down market movements. The null hypothesis is H_{07}: $\lambda^1_{11} = \lambda^2_{11}$; $\lambda^1_{12} = \lambda^2_{12}$; $\lambda^1_{13} = \lambda^2_{13}$; $\lambda^1_{21} = \lambda^2_{21}$; $\lambda^1_{22} = \lambda^2_{22}$; $\lambda^1_{23} = \lambda^2_{23}$. The test statistic values are given in the last column of Table 4.9. It is evident that this null hypothesis is rejected only in 3 pairs (Brazil-China, Russia-India, and Russia - China) in E-E combination and 5 pairs (US-China, UK-China, Hong Kong-Brazil , Hong Kong-China and Japan-China) in D-E combination. This gives overwhelming empirical support to the fact that differential effects of the 2 market movements considered in our proposed model - up and down - are very relevant and important for modelling risk return relationships in bivariate set-up. More explicitly, we note that among the pairs in D-D combination, there is no pair where any of these parameters has been found to be equal in the two market conditions, indicating thereby the importance of our model for this combination, in particular. And obviously, the same conclusion holds for both E-E and D-E combinations except for the few cases mentioned above.

Table 4.7: Wald test statistic values for absence as well as equality of BTGARCH-in-Mean Spillovers

Hypothesis	11	12	13	14	15
Developed-Developed (D-D) combination					
US-UK	0.1035	1.9828	3.8134	6.5399	16.1552
	(0.95)	(0.37)	(0.15)	(0.04)	(0.01)
US-HO	2.3846	10.2681	7.5172	11.6875	6.9933
	(0.30)	(0.01)	(0.02)	(0.00)	(0.32)
US-JAP	1.9728	4.3427	14.1825	31.3314	13.0932
	(0.37)	(0.11)	(0.00)	(0.00)	(0.04)
UK-HO	8.4176	1.2271	11.9620	5.7942	11.5532
	(0.01)	(0.54)	(0.00)	(0.06)	(0.07)
UK-JAP	7.0912	139.8848	99.9823	641.9872	1437.6339
	(0.03)	(0.00)	(0.00)	(0.00)	(0.00)
HO-JAP	1.1001	4.5425	2.9245	1.4649	13.7263
	(0.58)	(0.10)	(0.23)	(0.48)	(0.03)
Emerging-Emerging (E-E) combination					

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Hypothesis	11	12	13	14	15
BR-RUS	0.5835	1.2029	2.9992	8.7746	7.9178
	(0.75)	(0.55)	(0.22)	(0.01)	(0.24)
BR-IND	6.6814	7.4046	2.0638	5.0093	27.8208
	(0.04)	(0.02)	(0.36)	(0.08)	(0.00)
BR-CH	1.9197	2.2468	0.9266	10.9520	2.4821
	(0.38)	(0.33)	(0.63)	(0.00)	(0.87)
RUS-IND	1.9746	22.5188	4.8071	10.2852	10.5559
	(0.37)	(0.00)	(0.09)	(0.01)	(0.10)
RUS-CH	1.2567	14.0863	1.0718	1.1037	12.1372
	(0.53)	(0.00)	(0.59)	(0.58)	(0.06)
IND-CH	1.3858	12.9805	2.4956	2.5181	2.0378
	(0.50)	(0.00)	(0.29)	(0.28)	(0.92)
Developed-Emerging (D-D) combination					
US-BR	6.7590	0.5555	0.1885	0.5375	5.0153
	(0.03)	(0.76)	(0.91)	(0.76)	(0.54)
US-RUS	2.1732	1.2611	7.4725	4.7688	2.4842
	(0.34)	(0.53)	(0.02)	(0.09)	(0.87)
US-IND	2.0721	3.4927	0.5655	0.3573	11.8848
	(0.35)	(0.17)	(0.75)	(0.84)	(0.06)
US-CH	1.1829	0.7334	1.4196	2.4014	3.1545
	(0.55)	(0.69)	(0.49)	(0.30)	(0.79)
UK-BR	10.7200	0.1065	2.6444	2.2481	7.3061
	(0.00)	(0.95)	(0.27)	(0.32)	(0.29)
UK-RUS	5.5046	7.5297	8.5539	10.8690	21.8834
	(0.06)	(0.02)	(0.01)	(0.00)	(0.00)
UK-IND	31.3398	28.2393	29.7510	42.0164	80.1770
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-CH	0.7234	3.5364	0.0598	1.2933	4.9297

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Hypothesis	11	12	13	14	15
	(0.70)	(0.17)	(0.97)	(0.52)	(0.55)
HO-BR	5.2120	2.9050	2.3318	4.4924	7.5041
	(0.07)	(0.23)	(0.31)	(0.11)	(0.28)
HO-RUS	0.1695	0.6822	0.4205	0.8192	2.5274
	(0.92)	(0.71)	(0.81)	(0.66)	(0.87)
HO-IND	2.8127	1.7070	19.0765	8.1705	16.5982
	(0.25)	(0.43)	(0.00)	(0.02)	(0.01)
HO-CH	0.5849	6.1093	5.6133	26.5620	30.6023
	(0.75)	(0.05)	(0.06)	(0.00)	(0.00)
JAP-BR	43.3599	21.1202	1.1333	10.4189	14.3917
	(0.00)	(0.00)	(0.57)	(0.01)	(0.03)
JAP-RUS	4.5103	3.2965	1.6686	2.6212	3.7948
	(0.10)	(0.19)	(0.43)	(0.27)	(0.70)
JAP-IND	4.1435	9.2690	13.9708	9.4310	28.4539
	(0.13)	(0.01)	(0.00)	(0.01)	(0.00)
JAP-CH	6.0546	6.0843	2.5506	6.2141	16.2839
	(0.05)	(0.05)	(0.28)	(0.04)	(0.01)

Note: $p-$values are given in parenthesis.

4.6 Conclusions

In this chapter we have generalised the model for stock returns proposed in Chapter 3 in the bivariate set-up. In other words, we have proposed a model which has been called as the TVAR-BTGARCH-M model where asymmetry in conditional variance and different effects of the two market conditions, up and down, on conditional mean have been incorporated in case of returns on two stock markets. Unlike the univariate model in Chapter 3, the asymmetry in conditional variance has been considered in terms of the threshold GARCH model. Obviously, the consideration to 'in-mean' component in the model allows for the risk to affect the conditional mean directly. Also, study of the risk-return relationship involving two return series together helps in findings the spillover effects of one market on the other in terms of conditional mean, conditional variance as well as 'volatility-in-mean' component.

There are in all 28 pairs of countries - made out of 4 developed and 4 emerging (BRIC) countries - where this model has been applied. For the purpose of meaningful discussions, these pairs have been categorised into 3 combinations *viz.*, developed-developed (D-D), emerging-emerging (E-E) and developed-emerging (D-E). Along with the TVAR-BTGARCH-M model, we have also estimated 4 other models *viz.*, the VAR-BGARCH, VAR-BGARCH-M, VAR-BTGARCH-M, TVAR-BGARCH-M so as to be able to empirically investigate the usefulness and efficacy of the proposed model. It is to be noted that in case of GARCH or similar other volatility models in multivariate case, there are basically two different models for the conditional variance-covariance matrix, and accordingly the two approaches are called the BEKK and the dynamic conditional correlation (DCC) approaches. We first summarise the findings on the models by the BEKK approach. Different hypotheses of interests, especially, those concerning different effects of up and down market conditions on the various spillover effects, have also been tested in this chapter.

The first major finding in this chapter is that in many cases the parameters in the conditional mean part of the model are significant across the two market conditions, and that these are significantly different for a number of pairs. The findings in the 3 combinations are more or less the same. Of course, there are some cases where the market movements are found to be not significant in all the three combinations. The symmetric component of volatility has been found to be significant in all 28 combinations, as expected. The well-known fact of asymmetry in stock returns, which is often due to leverage effect, has been found to be overwhelmingly present in this study.

Insofar as the spillover effects are concerned, all the 3 kinds of spillovers have been found to be significant in many of the 28 pairs, although the respective numbers are not the same. The incidence of one market affecting the other in respect of one or both market conditions through mean spillover effects is found to be quite prevalent. There are only a few pairs where these spillover effects are found to be insignificant in both market conditions. On the other hand, these effects have been found to be significant in both market movements in a few pairs. Across the 3 combinations, it is found that in the D-E combination the spillover effects from developed to emerging is more often than it is in the reverse direction. The volatility as well as cross volatility spillovers are found to be very important in this model. In fact, both in terms of direct and indirect spillovers in variance, the findings are very strong in all the 3 combinations although in case of E-E combination, there are pairs where one of the direct and indirect effects is found to be absent.

In respect of 'BTGARCH-in-mean' effect, we have found that the spillovers of direct/indirect risk of one market on the mean returns of the other market in respect of the two market conditions is quite prevalent although it is insignificant in a few cases as well, especially in D-E combination. It is quite natural that the risk associated with the stock markets of emerging economies does not have significant effect on the up and down market conditions of developed economies as often as the effect in the reverse direction i.e., from developed to emerging economies, occurs. In fact, this is what has been observed as well. These spillover effects are absent completely in a few pairs in case of emerging to developed market while there are some pairs where spillovers in the reverse direction are absent. On the whole, we, therefore, conclude that different kinds of spillover effects, that too concerning up and down market movements as well, are very important in modelling returns of two stock markets together.

Finally, it is noted that the log-likelihood value is maximum for the proposed model in comparison to the other four restricted models. Although the difference in the maximized log-likelihood value is not significant in a few cases, the importance of the proposed model from statistical consideration is established for most of the pairs. It is thus established that the modelling issues considered in this study *viz.*, up and down market movements, asymmetric variance and direct effect of risk on conditional mean, are indeed important in studying the risk-return relationship in the bivariate set-up.

Chapter 5

Smooth Transition VAR - Bivariate Threshold GARCH-in-Mean Model: The DCC Approach

5.1 Introduction

In the preceding chapter, we have discussed, quite in detail, that stock markets around the world have increasingly become integrated and consequently studies on the transmission of return movements along with spillover effects involving major markets have gained momentum and become important. In that context, we have proposed a model in that chapter in MGARCH-in-mean framework where asymmetry in conditional variance and differential effects of two market situations - up and down - have been considered. In that model, named as the TVAR-BTGARCH-M model, the BEKK specification of the conditional variance-covariance matrix on returns, H_t, has been used. The study in this chapter considers basically the same modelling framework, but it uses the dynamic conditional correlation approach instead of the BEKK approach. There is another difference, although not a major one from modelling consideration *viz.*, instead of considering threshold VAR for the conditional mean model, the smooth transition VAR model is applied here. In other words, in this chapter, we use the correlation dynamics in returns in studying the risk-return relationship incorporating the two characteristics of returns, as mentioned above, in the multivariate set-up.

In the dynamic conditional correlation (DCC) model, the conditional correlation matrix is assumed to be time dependent. This model as well as its precursor, known as the constant conditional correlation

(CCC) model, where conditional correlations are assumed to be constant, may be viewed as nonlinear combinations of the univariate GARCH/EGARCH/TGARCH models. These two models allow for specification of individual conditional variances as well as conditional correlation matrix capturing the dependences between two series. The assumption that the conditional correlations are constant may seen unrealistic in many practical applications. In fact, it is now well-established that correlations between two stock returns are not constant through time. Correlations tend to rise with economic or equity market integration (see, for instance, Erb *et al.* (1994), Longin and Solnik (1995), and Goetznmann *et al.* (2005)). In the context of bull-bear markets, correlations tend to decline in bull market and increase in bear market (see, for details, Longin and Solnik (2001), and Ang and Bekaert (2002)). Longin and Solnik (1995, 2001) showed that correlations between markets increase during periods of high volatility, with the result that correlation would be higher than average exactly in the moment when diversification promises to yield gains. Consequently, such changes in correlation imply that the benefits to portfolio diversification may be rather modest during bear markets (*cf.* Baele (2005)). Of late, there have been quite a few works where DCC models based on GARCH and EGARCH models. For instance, Arouri *et al.* (2010) have analysed time variations in the comovements of Latin American stock markets where conditional correlations have been estimated from the DCC GARCH model. Pesaren and Pesaren (2010) have also used the DCC model proposed by Engle (2002) in their study on stock market crash in 2008. In the context of studying contagion or market interdependences, Amhad *et al.*(2013), have applied the DCC model involving some Euro and BRIICKS countries. Some other references on this topic are: Wang *et al.* (2007), Asai (2012), Celik (2012), Gjika and Horvath (2013), Lyocsa *et al.* (2012) and Lean and Teng (2013).

The organization of this chapter is as follows. In the next section, we discuss about the models and methodology used in this chapter, The empirical results are discussed in Section 5.3. This chapter closes with some concluding observations in Section 5.4.

5.2 The Proposed Model and Methodology

The basic framework of the model proposed in this chapter, as already mentioned in the preceding section, is the same as in Chapter 4. It differs only in respect of the form of H_t, the conditional variance-covariance matrix of r_t, which is now given by the dynamic conditional correlation (DCC) matrix, and the conditional mean model is the smooth transition VAR (STVAR) model. In this section, we first describe the constant as well as the dynamic conditional correlation models and then specify our proposed model.

5.2.1 Constant and dynamic conditional correlation representations

Bollerslev (1990) proposed a class of MGARCH model in which the conditional correlations are taken to be constant and hence the conditional covariances are proportional to the product of the corresponding conditional standard deviations. These restrictions greatly reduce the number of unknown parameters and thus simplify the estimation of the model.

The constant conditional correlation (CCC) model of H_t, based on N stock returns, is defined as:

$$H_t = D_t R D_t = (\rho_{ij}\sqrt{h_{iit}h_{jjt}}) \tag{5.1}$$

where $D_t = diag(h_{11t}^{1/2}, \ldots, h_{NNt}^{1/2})$, h_{iit} is any univariate conditional variance model - most often taken to be the symmetric GARCH but can as well be an asymmetric GARCH specification like the EGARCH or TGARCH and $R = (\rho_{ij})$ is a symmetric positive definite matrix whose elements are the constant conditional correlation ρ_{ij}. The original CCC model has the GARCH(1,1) specification for each conditional variance in D_t i.e.,

$$h_{iit} = \omega_i + \alpha_i \varepsilon_{i,t-1}^2 + \beta_i h_{iit-1}, \qquad i = 1, \ldots, N. \tag{5.2}$$

The H_t matrix defined in equation (5.1) is positive definite if and only if all the N conditional variances are positive and R is positive definite. The unconditional variances are easily obtained, as in the univariate case, but the unconditional covariances are difficult to calculate because of the nonlinearity involved in equation (5.1). He and Terasvirta (2002) used a VEC-type formulation for $(h_{11t}, h_{22t}, \ldots, h_{NNt})'$, to allow for interactions between the conditional variances, and they called the resultant model as the extended CCC model.

It is quite obvious that the assumption of conditional correlations being constant is unrealistic in many empirical applications. Christodoulakis and Satchell (2002), Engle (2002), and Tse and Tsui (2002) proposed generalizations of the CCC model by making the conditional correlation matrix time dependent. Accordingly, the DCC model is defined as

$$H_t = D_t R_t D_t = (\rho_{ijt}\sqrt{h_{iit}h_{jjt}}) \tag{5.3}$$

where $R_t = (\rho_{ijt})$, ρ_{ijt} being the time dependent conditional correlation. The requirement that this H_t is positive definite is guaranteed under simple conditions on the parameters, as stated in Bawens *et al.* (2006).

The DCC model of Christodoulakis and Satchell (2002) uses the Fisher transformation of the correlation coefficient. This model which is only for a bivariate set-up, is easy to implement because the property of positive definiteness of the conditional correlation matrix is guaranteed by the Fisher transformation. The DCC models of Tse and Tsui (2002) and Engle (2002), on the other hand, are genuinely multivariate and are useful when modelling high-dimensional data sets. Though in our actual empirical study, we consider returns on two stock markets i.e., we take bivariate combinations of the eight markets considered in this thesis, we take the DCC model of Engle (2002) for our study. The model by Engle (2002) has several advantages compared to other such models. First, it is less restrictive in terms of number of variables included in the model. Second, it accounts for heteroscedasticity by estimating the dynamic correlation coefficients of the standardised residuals. The DCC model of Engle (2002), denoted by $\mathrm{DCC_E}(1,1)$, is given as

$$R_t = diag(q_{11,t}^{-1/2}, \ldots, q_{NN,t}^{-1/2}) Q_t diag(q_{11,t}^{-1/2}, \ldots, q_{NN,t}^{-1/2}) \tag{5.4}$$

where the $N \times N$ symmetric positive definite matrix $Q_t = (q_{ij,t})$ is given by:

$$Q_t = (1 - \varphi_1 - \varphi_2)\bar{Q} + \varphi_1 \varepsilon_{t-1}^* \varepsilon_{t-1}^{*\prime} + \varphi_2 Q_{t-1} \tag{5.5}$$

where $\varepsilon_t^* = (\varepsilon_{1t}^*, \ldots, \varepsilon_{Nt}^*)$, $\varepsilon_{it}^* = \varepsilon_{it}/\sqrt{h_{iit}}, \quad i = 1, \ldots, N$ and ε_{it} is the random term associated with the proposed model for r_t, as given in equation (5.6) which follows. $\bar{Q}$ is the $N \times N$ unconditional variance-covariance matrix of ε_t^*, and φ_1 and φ_2 are non-negative scalar parameters satisfying $\varphi_1 + \varphi_2 < 1$. It may be noted that unlike the DCC model of Tse and Tsay (2002), this model has the advantage that it does not formulate the conditional correlation as a weighted sum of past correlations. In fact, the matrix Q_t is written as a GARCH equation and then transformed to a correlation matrix. Note that when $\varphi_1 = \varphi_2 = 0$, the $\mathrm{DCC_E}$ model reduces to the CCC model. This condition can, therefore, be tested for checking if imposing conditional correlations to be constant is empirically relevant.

Engle (2002) has taken h_{iit} to be an univariate GARCH model as in equation (5.2), and then stated the following conditions on the parameters for H_t to be positive definite for all t: (i) $\omega_i > 0$, (ii) $h_{ii,0} > 0$, (iii) α_i and β_i are such that h_{iit} will be positive with probability one, $i = 1, \ldots, N$, (iv) the roots of the polynomial of GARCH equation lie outside the unit circle, (v) $\varphi_1 > 0$, (vi) $\varphi_2 > 0$, and (vii) $\varphi_1 + \varphi_2 < 1$.

5.2.2 The proposed STVAR-BTGARCH-M model

As stated in the beginning of the section, the proposed model in this chapter, has basically the same framework as in case of the TVAR-BTGARCH-M model in Chapter 4 with H_t being as given in equation

(5.3), and the conditional mean equation being the smooth transition VAR (STVAR) instead of TVAR. It may be recalled that while proposing the STAR-EGARCH-M model for univariate analysis in Chapter 3, we noted that the advantage of using a smooth transition instead of indicator function is that the former allows for a gradual transition between different regimes (in our case, the two different market movements - up and down) by replacing the indicator function by a continuous function $G(\bar{r}_t^k, \gamma)$, most often the logistic function, which changes smoothly from 0 to 1 as $\bar{r}_t^k$ increases (see, for details Teresvirta (1994)). Keeping this modelling advantage in mind, we are considering smooth transition in the multivariate set-up for the conditional mean model where due consideration is given to up and down market movements. As in the preceding chapter, we are considering our proposed model for bivariate stock markets only, and accordingly the proposed STVAR-BTGARCH-M model, in the line of TVAR-BTGARCH-M model (*cf.* equation (4.6) of Chapter 4), is given by

$$\begin{aligned} r_t = &\left(a^1 + B^1 r_{t-1} + \Lambda^1 \text{vech}\,(H_t)\right) \odot (\mathbf{1} - \boldsymbol{G}[\cdot]) \\ &+ \left(a^2 + B^2 r_{t-1} + \Lambda^2 \text{vech}\,(H_t)\right) \odot \boldsymbol{G}[\cdot] + \varepsilon_t \end{aligned} \tag{5.6}$$

where, $\boldsymbol{G}[\cdot] = \begin{pmatrix} g(\bar{r}_{1t}^k, \gamma_1) \\ g(\bar{r}_{2t}^k, \gamma_2) \end{pmatrix}$, $g(\bar{r}_{it}^k, \gamma_i)$, $i = 1, 2$, are the usual logistic function (also given in Chapter 3) with parameters γ_1 and γ_2 corresponding to up and down market movements, respectively. H_t is the conditional variance-covariance matrix of DCC model as given in equation (5.3), and all other notations are as defined in the preceding chapter.

A useful feature of the DCC model is that this can be estimated consistently using a two-step procedure (see,Engle and Sheppard (2001), and Bauwens *et al.*, (2006), for details) Under the assumption of bivariate normality of $\varepsilon_t|\psi_{t-1}$ i.e., $\varepsilon_t|\psi_{t-1} \sim N(0, H_t)$, the log-likelihood function (up to a constant), based on T sample observations is given as:

$$L(\theta) = -\frac{1}{2}\sum_{t=1}^{T}(\ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t). \tag{5.7}$$

Obviously, obtaining ML estimates involves maximizing the log-likelihood function for the T observations with respect to the vector of all parameters of the model,θ. Since the objective function involved is highly nonlinear, the necessary part of the program was written in Gauss.

5.3 Empirical Results

The proposed model STVAR-BTGARCH-M, specified in equations (5.6) through (5.3), which is based on the DCC approach, has been estimated by the ML method of estimation, as mentioned in the preceding section, using returns on daily frequency from eight stock markets for the period 01 January 2000 to 31 December 2012. The estimates of the parameters of the model are presented in Table 5.1. It may be mentioned that we also carried out estimation of the parameters of another model, called the STVAR-BGARCH-M model, where the market movements are duly modelled in the mean part while the variance-covariance matrix is taken to be symmetric bivariate GARCH[1]. The purpose of considering this model is to find to what extent asymmetry in H_t affects the performance as opposed to symmetric H_t when the DCC approach is being considered.

We first discuss about the estimates of the parameters of the conditional mean part of the model. It is evident that almost all parameters in the two market conditions are significant for all the 3 combinations (D-D, E-E, and D-E). Thus the evidence of mean spillover effect from one stock market to another is overwhelming irrespective of the combination of countries considered. In particular, in case of D-D combination, this effect is significant in both directions in down market for all the 6 pairs of markets. In case of up market, except for the UK-Hong Kong, the UK-Japan and Hong Kong-Japan pairs - in each case in one direction only - the effect is significant for all other pairs. An interesting observation is that unlike in the BEKK approach, the spillover effects in down market from the first stock market to the second (both developed) are negative in all 6 pairs.

In the E-E combination of countries, the mean spillover effects, at least in one direction, for all the pairs are significant combining both up and down markets in both directions. Further, in this combination, the mean spillover effect is significant and positive in down market from Brazil to Russia, Brazil to India, Brazil to China, Russia to India, India to China, and China to India. In the up market, there are only two pairs – from China to Russia, and China to India – where the spillover effect is found to be negative. In cases of India to Brazil, China to Brazil, and India to Russia, this effect is insignificant. In all the remaining pairs in this market condition, this spillover effect is positive.

The scenario for the D-E combination is a little different. Here, there are quite a few pairs where the spillover effect is found to be insignificant in either of up and down markets - but all in one direction. There are only 3 pairs where the spillover effect is negative yet significant. These pairs along with

[1]We are not presenting the estimates of STVAR-BTGARCH-M model separately since for the purpose in mind the maximized log-likelihood values of the model for the different pairs are sufficient for statistical conclusions.

directions of effects are: from UK to Brazil, UK to China, Hong Kong to China, Japan to Brazil, Japan to China, and Japan to India - all but one of these are in down market condition. Thus, on the whole, we find that in this DCC approach as well, the market conditions like up and down are found to be important in modelling stock returns, and that mean spillover is affected by such market conditions.

Now looking at the parameters of smoothness i.e., γ_1 and γ_2, we find that these two parameters are significant for all pairs in all the 3 combinations of markets. The parameter values in no combinations of pairs have been found to be either closed to zero or very high. Thus, the validity of consideration of smooth transition in the conditional mean from down market movement to up market movement is empirically established for all the 28 bivariate pairs.

Table 5.1: Estimates of the parameters of STVAR(1)-BTGARCH-M model

A: Parameters in the conditional mean component												
	Parameters in the VAR part						Parameters in the BTGARCH-in-mean part					
	a_1^1	b_{11}^1	b_{12}^1	a_2^1	b_{21}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
Developed-Developed (D-D) combination												
US-UK	0.0558	-0.0133	-0.0726	-0.171	0.3364	-0.2614	0.0125	-0.0401	0.025	0.0055	-0.0482	0.0323
	(0.03)	(0.65)	(0.00)	(0.00)	(0.00)	(0.00)	(0.62)	(0.00)	(0.18)	(0.85)	(0.34)	(0.18)
US-HO	-0.222	-0.0796	0.072	-0.1465	0.5494	-0.0741	0.0289	0.0395	-0.0221	0.0219	0.107	-0.0344
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.02)	(0.04)	(0.05)	(0.19)	(0.00)	(0.01)
US-JAP	-0.2397	-0.1175	-0.0276	-0.1535	0.492	-0.0304	0.0212	0.0793	-0.035	-0.0224	0.1082	0.028
	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.03)	(0.09)	(0.00)	(0.01)	(0.09)	(0.00)	(0.03)
UK-HO	0.0307	-0.0367	-0.0303	-0.0375	0.342	-0.1922	-0.0173	0.13	-0.0207	-0.0618	0.1801	-0.0137
	(0.03)	(0.15)	(0.08)	(0.02)	(0.00)	(0.00)	(0.12)	(0.00)	(0.02)	(0.00)	(0.00)	(0.17)
UK-JAP	0.0409	-0.053	0.0216	-0.0528	0.3563	-0.132	-0.0401	0.1264	-0.0041	-0.1151	0.1943	0.0199
	(0.00)	(0.02)	(0.25)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.67)	(0.00)	(0.00)	(0.03)
HO-JAP	0.0105	-0.0663	0.0338	-0.0888	0.0264	-0.0253	-0.0527	0.1556	-0.0469	-0.0814	0.2125	-0.0377
	(0.33)	(0.00)	(0.01)	(0.00)	(0.01)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Emerging-Emerging (E-E) combination												
BR-RUS	-0.1157	-0.0452	0.0141	0.2068	0.1144	-0.0387	0.0557	-0.1037	0.0156	-0.0117	-0.0494	0.0131
	(0.00)	(0.04)	(0.44)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.07)	(0.43)	(0.00)	(0.25)
BR-IND	-0.0629	-0.0395	0.0232	0.1243	0.093	0.0074	0.035	-0.0261	-0.0043	-0.0285	-0.0353	0.027
	(0.25)	(0.05)	(0.33)	(0.00)	(0.00)	(0.76)	(0.04)	(0.62)	(0.78)	(0.02)	(0.17)	(0.10)
BR-CH	-0.0841	-0.0145	-0.0181	-0.2533	0.0451	-0.0325	0.0287	-0.0633	0.0097	0.002	-0.0237	0.0645
	(0.01)	(0.25)	(0.28)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)	(0.49)	(0.83)	(0.02)	(0.00)
RUS-IND	0.164	0.004	-0.0202	0.0047	0.0921	-0.0309	0.012	-0.019	-0.0152	-0.001	-0.0264	0.0129
	(0.03)	(0.82)	(0.50)	(0.89)	(0.00)	(0.14)	(0.27)	(0.36)	(0.24)	(0.85)	(0.11)	(0.36)
RUS-CH	0.0956	0.0056	0.0029	-0.2546	0.0016	-0.0218	0.0084	-0.0547	-0.0051	0.0056	-0.0663	0.0677
	(0.02)	(0.59)	(0.92)	(0.00)	(0.93)	(0.08)	(0.36)	(0.00)	(0.73)	(0.24)	(0.00)	(0.00)
IND-CH	-0.0265	-0.013	0.019	0.037	0.0196	-0.0029	0.0194	-0.0653	-0.0057	-0.0007	-0.0342	-0.0174
	(0.01)	(0.36)	(0.09)	(0.01)	(0.05)	(0.77)	(0.05)	(0.00)	(0.59)	(0.94)	(0.00)	(0.08)
Developed-Emerging (D-E) combination												
US-BR	0.033	-0.0215	-0.1676	-0.16	-0.0091	-0.0243	-0.0073	0.1876	-0.084	-0.0857	0.2263	-0.0271
	(0.79)	(0.78)	(0.00)	(0.28)	(0.90)	(0.61)	(0.96)	(0.58)	(0.39)	(0.62)	(0.57)	(0.81)
US-RUS	-0.1154	-0.1833	-0.0539	-0.0454	0.2637	-0.0568	0.2172	-0.4829	0.0248	0.3744	-1.2657	0.1277
	(0.04)	(0.01)	(0.19)	(0.78)	(0.00)	(0.28)	(0.00)	(0.00)	(0.18)	(0.00)	(0.00)	(0.00)
US-IND	-0.0316	-0.0864	-0.0461	0.0076	0.2319	-0.0123	0.0142	-0.003	-0.002	-0.0256	0.042	0.0061
	(0.16)	(0.00)	(0.00)	(0.87)	(0.00)	(0.59)	(0.19)	(0.84)	(0.78)	(0.02)	(0.00)	(0.63)
US-CH	-	-	-	-	-	-	-	-	-	-	-	-

Continued on next page

Table: 5.1 Continued from previous page

	a_1^1	b_{11}^1	b_{12}^1	a_2^1	b_{21}^1	b_{22}^1	λ_{11}^1	λ_{12}^1	λ_{13}^1	λ_{21}^1	λ_{22}^1	λ_{23}^1
UK-BR	0.0195	-0.0885	0.0726	-0.12	0.0004	-0.0287	0	0.1645	-0.0504	-0.1345	0.3035	-0.0096
	(0.11)	(0.00)	(0.00)	(0.00)	(0.97)	(0.02)	(1.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.27)
UK-RUS	0.0562	-0.035	-0.0012	0.1808	-0.0129	0.0082	0.0738	-0.0723	-0.0017	0.069	-0.2002	0.0197
	(0.01)	(0.06)	(0.93)	(0.00)	(0.45)	(0.51)	(0.12)	(0.46)	(0.90)	(0.00)	(0.00)	(0.12)
UK-IND	0.0827	-0.0523	-0.0034	0.0577	0.1586	-0.0417	0.0711	-0.2079	0.0114	-0.0924	0.2929	-0.0325
	(0.00)	(0.05)	(0.83)	(0.44)	(0.00)	(0.17)	(0.02)	(0.02)	(0.22)	(0.00)	(0.00)	(0.07)
UK-CH	-0.01	-0.0331	-0.0219	-0.2551	0.0535	-0.0308	0.0072	0.1388	-0.0006	-0.0188	0.1104	0.0674
	(0.45)	(0.05)	(0.12)	(0.00)	(0.01)	(0.04)	(0.62)	(0.00)	(0.95)	(0.17)	(0.00)	(0.00)
HO-BR	0.0445	-0.086	0.2145	0.1296	-0.0264	-0.0221	0.0425	-0.0975	-0.0062	-0.004	0.1169	-0.0338
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.03)	(0.00)	(0.00)	(0.39)	(0.70)	(0.00)	(0.00)
HO-RUS	-0.0429	-0.0686	0.0891	0.1604	-0.0052	-0.0031	0.041	-0.0915	0.0074	-0.0399	0.1027	-0.0141
	(0.00)	(0.00)	(0.00)	(0.00)	(0.59)	(0.75)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)	(0.10)
HO-IND	-	-	-	-	-	-	-	-	-	-	-	-
HO-CH	0.0289	-0.0233	-0.025	-0.1618	-0.0531	-0.0131	-0.0434	0.2322	-0.0406	0.05	-0.4188	0.1328
	(0.22)	(0.33)	(0.28)	(0.01)	(0.00)	(0.51)	(0.00)	(0.00)	(0.01)	(0.10)	(0.02)	(0.00)
JAP-BR	-0.0384	-0.0668	0.2508	-0.1216	-0.0436	-0.0017	-0.0082	0.4215	-0.0838	-0.0433	0.241	0.0052
	(0.12)	(0.00)	(0.00)	(0.00)	(0.08)	(0.92)	(0.61)	(0.00)	(0.00)	(0.04)	(0.00)	(0.72)
JAP-RUS	-0.0432	-0.0581	0.1349	0.1222	-0.0172	0.014	-0.0115	0.1109	-0.0168	-0.0323	0.2392	-0.0317
	(0.10)	(0.00)	(0.00)	(0.12)	(0.36)	(0.39)	(0.42)	(0.00)	(0.00)	(0.04)	(0.00)	(0.01)
JAP-IND	-0.0837	-0.0436	0.0966	0.0141	0.098	-0.0069	0.0525	-0.1749	0.0364	-0.0639	0.2719	-0.0412
	(0.00)	(0.01)	(0.00)	(0.61)	(0.00)	(0.72)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
JAP-CH	0.0322	0.0341	-0.0468	-0.147	-0.0578	0.0117	-0.0277	0.1712	-0.0189	-0.0563	0.3712	0.0198
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.26)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.05)

B: Parameters of the second regime

	a_1^2	b_{11}^2	b_{12}^2	a_2^2	b_{21}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
Developed-Developed (D-D) combination												
US-UK	-0.032	-0.0988	0.0656	0.1214	0.3312	-0.0072	-0.0223	0.1391	-0.0537	-0.0615	0.0523	0.0305
	(0.24)	(0.00)	(0.00)	(0.00)	(0.00)	(0.76)	(0.56)	(0.00)	(0.06)	(0.05)	(0.02)	(0.09)
US-HO	0.1116	-0.0751	-0.0881	0.026	0.3776	-0.1609	0.0334	-0.0683	0.0427	-0.0782	0.0631	0.1252
	(0.00)	(0.00)	(0.00)	(0.44)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	0.1565	-0.0126	0.0351	0.1591	0.4539	-0.161	0.0308	-0.0433	0.0192	-0.0559	-0.1052	0.0025
	(0.00)	(0.50)	(0.01)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.14)	(0.00)	(0.00)	(0.93)
UK-HO	0.0028	-0.0679	0.017	-0.0169	0.3202	-0.0763	-0.0151	-0.0454	0.0052	0	-0.1725	0.0905
	(0.92)	(0.00)	(0.21)	(0.76)	(0.00)	(0.00)	(0.17)	(0.04)	(0.68)	(1.00)	(0.00)	(0.00)
UK-JAP	0.0401	-0.0407	-0.006	0.1322	0.4044	-0.1271	0.0148	-0.0879	-0.0134	-0.1464	0.1098	-0.0126
	(0.03)	(0.03)	(0.64)	(0.00)	(0.00)	(0.00)	(0.35)	(0.00)	(0.34)	(0.00)	(0.00)	(0.75)
HO-JAP	0.126	0.0337	-0.093	0.1523	-0.0223	-0.018	0.0342	-0.0701	-0.0176	0.028	0.1211	-0.1633
	(0.00)	(0.00)	(0.00)	(0.00)	(0.19)	(0.08)	(0.00)	(0.00)	(0.07)	(0.04)	(0.00)	(0.00)
Emerging-Emerging (E-E) combination												
BR-RUS	0.3257	0.0171	0.0388	0.2473	0.2167	-0.0439	-0.1128	0.0779	-0.0014	-0.0162	-0.134	0.0324
	(0.00)	(0.46)	(0.02)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.88)	(0.20)	(0.00)	(0.00)
BR-IND	0.203	0.0309	0.0138	0.1802	0.1284	0.0125	-0.0197	0.0429	-0.0368	-0.0408	0.1358	-0.0121
	(0.00)	(0.20)	(0.46)	(0.00)	(0.00)	(0.42)	(0.40)	(0.00)	(0.11)	(0.15)	(0.12)	(0.72)
BR-CH	0.0826	0.0246	-0.0063	0.0613	0.101	-0.0274	-0.0108	0.052	-0.0001	-0.0082	-0.1279	0.0414
	(0.00)	(0.26)	(0.69)	(0.00)	(0.00)	(0.05)	(0.30)	(0.00)	(0.99)	(0.41)	(0.00)	(0.00)
RUS-IND	0.1862	0.0198	0.0237	0.1566	0.0705	0.0236	-0.0225	0.0323	-0.0082	0.0238	-0.0908	-0.0109
	(0.00)	(0.23)	(0.25)	(0.00)	(0.00)	(0.12)	(0.04)	(0.12)	(0.55)	(0.00)	(0.00)	(0.44)
RUS-CH	0.2374	0.0495	-0.0533	0.0132	0.0592	-0.0256	-0.0336	0.0724	-0.0083	0.0104	-0.1237	0.0224
	(0.00)	(0.01)	(0.00)	(0.37)	(0.00)	(0.02)	(0.00)	(0.00)	(0.40)	(0.11)	(0.00)	(0.06)
IND-CH	0.1386	0.026	-0.0257	0.0707	0.0408	-0.0112	0.0032	0.0998	-0.0136	0.0145	-0.1036	0.0179
	(0.00)	(0.01)	(0.06)	(0.00)	(0.00)	(0.31)	(0.74)	(0.00)	(0.16)	(0.14)	(0.00)	(0.12)
Developed-Emerging (D-E) combination												
US-BR	0.22	-0.0384	0.1344	0.3931	0.1583	-0.016	0.0324	-0.1433	-0.019	0.1552	-0.2152	-0.0576
	(0.07)	(0.59)	(0.00)	(0.04)	(0.02)	(0.71)	(0.82)	(0.57)	(0.79)	(0.41)	(0.61)	(0.64)

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Table: 5.1 Continued from previous page

	a_1^2	b_{11}^2	b_{12}^2	a_2^2	b_{21}^2	b_{22}^2	λ_{11}^2	λ_{12}^2	λ_{13}^2	λ_{21}^2	λ_{22}^2	λ_{23}^2
US-RUS	0.0923	0.0514	0.0401	0.3549	0.261	-0.0362	-0.2579	0.6028	-0.0341	-0.9162	2.9982	-0.296
	(0.12)	(0.48)	(0.28)	(0.01)	(0.00)	(0.42)	(0.00)	(0.00)	(0.10)	(0.00)	(0.00)	(0.00)
US-IND	0.0355	-0.0423	0.0071	0.1134	0.2957	0.0132	0.0173	0.093	-0.0315	0.0302	0.0825	-0.0187
	(0.03)	(0.02)	(0.55)	(0.00)	(0.00)	(0.35)	(0.19)	(0.00)	(0.00)	(0.11)	(0.00)	(0.33)
US-CH	-	-	-	-	-	-	-	-	-	-	-	-
UK-BR	0.1915	-0.0722	0.0735	0.3706	0.1331	-0.0491	-0.0104	-0.103	-0.0337	0.1005	-0.2508	-0.0468
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.31)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-RUS	0.027	-0.0805	0.0143	0.2646	0.0344	0.0059	-0.0737	0.0629	-0.0091	-0.1034	0.0407	-0.0138
	(0.26)	(0.00)	(0.06)	(0.00)	(0.35)	(0.72)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.39)
UK-IND	0.1483	-0.0515	0.0145	0.1761	0.1482	0.0092	-0.1177	0.3341	-0.0879	-0.0857	0.5394	-0.0932
	(0.00)	(0.01)	(0.41)	(0.00)	(0.00)	(0.65)	(0.00)	(0.00)	(0.00)	(0.03)	(0.00)	(0.00)
UK-CH	0.0132	-0.046	0.0141	0.0061	0.1633	-0.0353	-0.0024	-0.1458	0.0014	0.0163	-0.1318	0.0326
	(0.70)	(0.00)	(0.19)	(0.86)	(0.00)	(0.03)	(0.91)	(0.00)	(0.86)	(0.20)	(0.00)	(0.03)
HO-BR	0.1701	-0.0857	0.1965	0.1675	0.0489	-0.0372	0.0381	-0.097	-0.0391	0.0043	-0.1262	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.69)	(0.00)	(0.92)
HO-RUS	-0.0123	-0.0302	0.0763	0.2434	0.0094	0.0237	0.057	-0.0626	0.0059	-0.0177	-0.113	0.0101
	(0.65)	(0.00)	(0.00)	(0.00)	(0.47)	(0.16)	(0.00)	(0.00)	(0.32)	(0.17)	(0.00)	(0.33)
HO-IND	-	-	-	-	-	-	-	-	-	-	-	-
HO-CH	0.0181	0.0275	-0.0033	0.0173	0.0169	-0.012	0.096	-0.2316	0.0156	-0.0284	0.2304	-0.025
	(0.73)	(0.16)	(0.83)	(0.83)	(0.48)	(0.59)	(0.00)	(0.00)	(0.24)	(0.30)	(0.06)	(0.49)
JAP-BR	0.164	-0.1003	0.1777	-0.1116	0.0593	0.0253	0.0501	-0.1138	-0.0445	0.0217	-0.0249	0.0504
	(0.01)	(0.00)	(0.00)	(0.39)	(0.02)	(0.28)	(0.10)	(0.00)	(0.00)	(0.12)	(0.78)	(0.13)
JAP-RUS	0.0606	-0.0648	0.1059	0.2229	0.0154	0.0296	0.0175	-0.0808	-0.002	0.0427	-0.2769	0.0119
	(0.12)	(0.00)	(0.00)	(0.00)	(0.53)	(0.09)	(0.31)	(0.00)	(0.76)	(0.01)	(0.00)	(0.40)
JAP-IND	0.0483	-0.0758	0.0948	-0.0738	0.0291	0.0076	0.1743	-0.3812	-0.0083	-0.0533	0.8097	-0.1531
	(0.45)	(0.00)	(0.00)	(0.07)	(0.16)	(0.72)	(0.00)	(0.00)	(0.72)	(0.04)	(0.00)	(0.00)
JAP-CH	0.2093	-0.0386	-0.0235	0.3531	0.0135	-0.0373	-0.017	-0.0656	-0.0294	-0.002	-0.218	-0.0382
	(0.00)	(0.00)	(0.10)	(0.00)	(0.38)	(0.00)	(0.08)	(0.00)	(0.00)	(0.87)	(0.00)	(0.01)

C: Parameters of the smoothness, TGARCH and DCC

	γ_1	γ_2	c_1	c_2	α_1	α_2	d_1	d_2	β_1	β_2	φ_1	φ_2
Developed-Developed (D-D) combination												
US-UK	2.491	2.1359	0.0402	0.0748	0.006	0.0295	0.1528	0.1053	0.8874	0.8883	0.0294	0.8639
	(0.00)	(0.00)	(0.00)	(0.00)	(0.50)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.06)	(0.00)
US-HO	1.9231	1.9054	0.0423	0.0899	-0.0224	0.0347	0.1904	0.1321	0.8993	0.8622	0.1909	0.2498
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-JAP	2.0027	4.0072	0.0404	0.12	-0.0246	0.0343	0.2023	0.1501	0.8984	0.8401	0.0027	0.2482
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.66)	(0.00)
UK-HO	2.538	2.5665	0.0398	0.076	0.0062	0.0335	0.1508	0.1035	0.8884	0.8853	0.0613	0.4716
	(0.00)	(0.00)	(0.00)	(0.00)	(0.45)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-JAP	2.4612	3.4653	0.0394	0.0967	0.0148	0.0608	0.1521	0.0929	0.8817	0.8584	0.0192	0.4283
	(0.00)	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.16)	(0.00)
HO-JAP	2.4861	3.5528	0.1163	0.2248	0.0399	0.0526	0.1239	0.1294	0.8594	0.8039	0.1598	0.4533
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Emerging-Emerging (E-E) combination												
BR-RUS	2.5545	2.0747	0.1865	0.223	0.0169	0.1054	0.1127	0.0842	0.8808	0.8201	0.4058	0.3285
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BR-IND	2.5934	1.9881	0.2567	0.3074	0.0212	0.0477	0.1186	0.2172	0.8548	0.7569	0.3334	0.5012
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
BR-CH	2.5912	2.0114	0.2531	0.1513	0.0195	0.0711	0.1288	0.0429	0.8532	0.8627	0.0736	0.2765
	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
RUS-IND	2.6032	2.0995	0.2746	0.3083	0.1105	0.0373	0.0699	0.2323	0.8129	0.7609	0.0511	0.3476
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
RUS-CH	2.5946	2.1138	0.2295	0.1403	0.1088	0.0702	0.0811	0.0428	0.8182	0.8671	-0.0067	0.3156
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
IND-CH	2.4713	2.0416	0.2984	0.2425	0.0476	0.0893	0.2133	0.0562	0.7624	0.811	0.1053	0.3979
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

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Table: 5.1 Continued from previous page

	γ_1	γ_2	c_1	c_2	α_1	α_2	d_1	d_2	β_1	β_2	φ_1	φ_2
Developed-Emerging (D-E) combination												
US-BR	2.6187	4.3861	0.0368	0.2057	-0.015	0.0268	0.1633	0.0999	0.9075	0.8682	0.2894	0.4691
	(0.00)	(0.07)	(0.00)	(0.00)	(0.05)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
US-RUS	2.2774	2.1451	0.0384	0.2264	-0.0135	0.0965	0.1682	0.087	0.9027	0.8244	0.1025	0.2702
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.17)
US-IND	12.579	11.2284	0.0445	0.3001	-0.0125	0.0351	0.1868	0.2296	0.8906	0.7627	0.0203	0.582
	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)
US-CH	-	-	-	-	-	-	-	-	-	-	-	-
UK-BR	2.4707	3.4937	0.034	0.2746	-0.004	0.0309	0.1477	0.1063	0.9046	0.8491	0.0937	0.3693
	(0.00)	(0.00)	(0.00)	(0.00)	(0.60)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-RUS	2.5346	2.5712	0.0366	0.2332	0.0012	0.1099	0.1542	0.0682	0.8947	0.821	0.0948	0.4585
	(0.00)	(0.00)	(0.00)	(0.00)	(0.86)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-IND	2.3731	3.442	0.0396	0.316	0.0152	0.0408	0.153	0.2162	0.8783	0.7557	0.2476	0.3831
	(0.00)	(0.00)	(0.00)	(0.00)	(0.09)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
UK-CH	2.4314	3.4612	0.0394	0.1522	0.0036	0.0689	0.1744	0.0441	0.8819	0.8632	0.0726	0.4279
	(0.00)	(0.00)	(0.00)	(0.00)	(0.64)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
HO-BR	5.4707	3.4937	0.0873	0.3288	0.0281	0.0304	0.1342	0.1225	0.8736	0.8294	0.1752	0.4645
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
HO-RUS	2.4851	3.503	0.0758	0.2312	0.0231	0.1117	0.1186	0.0668	0.8914	0.8236	-0.0215	0.4762
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(0.00)
HO-IND	-	-	-	-	-	-	-	-	-	-	-	-
HO-CH	2.4485	3.4955	0.077	0.1559	0.0223	0.067	0.1267	0.0517	0.8862	0.8608	0.2992	0.0393
	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.55)
JAP-BR	2.4811	3.4648	0.1117	0.3188	0.0333	0.0137	0.1409	0.157	0.8537	0.8307	0.122	0.3606
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.12)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)	(0.00)
JAP-RUS	2.4809	3.4603	0.1171	0.2404	0.0292	0.1125	0.1344	0.0687	0.8607	0.8206	-0.0117	0.3687
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.04)	(0.00)
JAP-IND	2.6883	3.2436	0.1323	0.3548	0.0494	0.0344	0.0985	0.244	0.8513	0.7428	0.1615	0.6733
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
JAP-CH	2.5487	3.5357	0.1294	0.1674	0.0308	0.0698	0.1444	0.0484	0.8494	0.8561	0.082	0.4417
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

$p-$values are given in parenthesis.

Insofar as the behaviour of conditional variance as captured through the BTGARCH model is concerned, we note that the parameters in the GARCH component of the model *viz.*, α_1, α_2, β_1, and β_2 are all significant in all the three combinations of markets except for α_1 in US -UK and UK- Hong Kong , UK- Brazil and UK-Russia and UK -China, and α_2 for Japan-Brazil pair only. The overwhelming significance of the variance parameters is only expected. Now, looking at d_1 and d_2, the two coefficients capturing asymmetry (leverage effect) in the conditional variance, we note that these 2 parameters are highly significant for all pairs in the three combinations. Like in the case of the BEKK approach, this establishes that consideration of asymmetry in studying the risk-return relationship in bivariate set-up is found to be extremely important in case of DCC approach as well.

As regards, the conditional correlations across any two of these markets, we find that the parameters, φ_1 and φ_2, are both significant in all pairs of stock markets except for US-Japan, UK-Japan and Japan-Brazil, and US-Russia where one of these two parameters is insignificant. Thus, we can conclude that conditional correlations are indeed dynamic in nature and also highly significant, and hence the DCC modelling approach, on the whole, yields an useful risk-return relation in the bivariate case.

Finally, we discuss about the spillover effects with reference to the 'BTGARCH-in-mean' component i.e., we note how the risk of one market affects the returns of another market in both up and down market situations. Looking at the D-D combination of stock markets, we find that the own spillover effects on this count are mostly significant. It is only in case of US-UK pair and UK-Hong Kong pair - both in down market - that we find neither of the markets in both cases have significant own spillover effects. In case of up market there are only 5 cases where own spillover effects are insignificant. These are US in US-UK pair, UK in UK-Hong Kong pair, UK in UK-Japan pair, Japan in US-Japan pair and Japan in UK-Japan pair. Similar is the finding for the 6 pairs in E-E combination in down market. In all, there are 4 cases where the own spillover effects are insignificant. These are: each of Russia and India in Russia-India pair, Russia in Brazil-Russia pair, and Russia in Russia-China pair. In case of up market in E-E combination, there are 6 such cases which are as follows: each of Brazil and India in Brazil-India pair, each of India and China in India-China pair, Brazil in Brazil-China pair, and India in Russia-India pair. In the D-E combination of pairs, we find that the own spillover effects is insignificant in the following cases in the down market: both US and Brazil have no own spillover effects, and so are the cases with US and India, UK and Russia, and Japan and Brazil. Also, Brazil in UK-Brazil pair, UK in UK-China pair and Japan in Japan-Russia pair show no own spillover effect. In case of up market, we note that there is no own spillover effect for both US and Brazil, US and India, and Japan and Russia. The other cases where only one country in a pair has no spillover effect of its own are: the UK in UK-Brazil, Russia in UK-Russia, UK in UK-China, Brazil in Hong Kong-Brazil, Russia in Hong Kong-Russia, and China in Hong Kong-China.

Now, looking at the estimates of λ_{21}^1 and λ_{13}^1 which stand for the cross (direct) spillover effects in down market, we find that in the D-D combination, this effect is significant both ways in all 6 cases except for risk of UK having no significant effect on mean return on US. This establishes that return of any developed stock market is significantly affected by the risk of another developed market except for the case(s) mentioned. We may also note that the estimates of all the coefficients are found to be positive except for US-UK pair. In the up market situation, the observations on the statistical significance of the 2 relevant parameters *viz.*, λ_{21}^2 and λ_{13}^2, are that for all combinations both the coefficients are significant. However, it is also to be noted that, λ_{21}^2 is found to have negative estimate for all but US-UK pair. As regards λ_{13}^2, there are two pairs (US-Japan and UK-Hong Kong) where the sign is negative. Insofar as the six pairs of E-E combination are concerned, except for λ_{21}^1 in case of Brazil-India, Russia-India, and λ_{13}^1 in Brazil-India, all others are significant. In particular, it may be noted that the risk of Brazil stock market does not affect the returns on Indian stock market and *vice versa*. One striking observation for this down market movement is that both the coefficients are found to be negative in all 6 pairs in this combination. In the up market situation, λ_{21}^2 is positive and significant in all but Russia -India pair while λ_{13}^2 is found to be negative and significant in all but Brazil-India pair. Finally, in the D-E combination we find that both the coefficients in both down and up markets are mostly significant. There are only few cases where the coefficients are insignificant. In US-Brazil pair, there is no cross spillover (direct) effect from either market on the other in the down market; other than this pair, λ_{21}^1 is insignificant in US-India and Uk-Russia pairs. In case of up market in D-E combination, US-Brazil pair has no such spillover effect from either direction, as in case of down market. The other two cases of insignificant coefficients are: λ_{21}^2 for US-India and λ_{13}^2 for Japan-Brazil. As regards the sign of these parameters in this combination, we note that there are a few pairs where the coefficients are negative in both up and down markets. Thus, it is found that taking all the three combinations of markets together the incidence of significance cross (direct) volatility is overwhelmingly present.

As regards the cross (indirect) spillovers in D-D combination, there are only 4 cases (for US-UK pair in both directions and for US-Hong Kong, and UK-Japan in one direction only) in down market and three cases (US-Japan, UK-Hong Kong, and UK-Japan in one direction only) in up market, which are insignificant. In case of E-E combination, the findings are quite in sharp contrast to those for D-D combination. Here in almost all cases in both market movements, the coefficients are insignificant. The only exceptions are λ_{12}^1 in case of Brazil-Russia pair, and λ_{22}^1 in case of Brazil-India for down market, and λ_{22}^2 for Russia-India. This shows that there is practically no indirect spillover effect between risk and return in case of markets in E-E combination. As for the D-E combination of markets, the coefficients are found to be insignificant in a number of cases in both market situations. There is no significant spillover effects in both directions for US-Brazil pair as well as for UK-China pair in down market. Further, λ_{12}^1 is insignificant in case of 6 pairs of markets. In the up market, US-Brazil, UK-China, Hong Kong-Russia and Hong Kong-China have no indirect spillover effects in either direction. It may be recalled that this is same as that of direct spillover effect. Also, λ_{12}^2 is found to be insignificant in 2 other pairs (Japan-Russia and Japan-India) while λ_{22}^2 is insignificant in 4 pairs (US-India, Hong Kong-Brazil, Japan-Brazil and Japan-China). It may thus be concluded that while the risk of one country (either developed or emerging) affects the returns of another country (either developed or emerging) in terms of indirect spillover i.e., spillovers through covariance terms, this effect is statistically significant for a good number of pairs of markets. It is at the same time true that in some pairs of countries this is statistically insignificant.

Before we conclude this chapter, we report the maximized log-likelihood values of the proposed model, the STVAR-BTGARCH-M model, along with those of another model *viz.*, the TVAR-BGARCH-M model in Table 5.2. The latter model, as the name suggests, incorporates the market movements in the conditional mean return but takes the conditional variances-covariances to be symmetric GARCH in bivariate set-up. The comparison between these two models has been done by the likelihood ratio (LR) test, and the findings suggest to what extent the model improves when asymmetry is considered in the conditional variance in the DCC approach. It is evident from the LR test statistic values that for all the 25 pairs[2] the proposed model has performed significantly better than the STVAR-BGARCH-M model. Thus, it establishes that for such bivariate models on risk-return relationship, asymmetry of conditional variance is very important in the DCC approach as well.

Table 5.2: LR test statistic values for testing STVAR-BGARCH-M models against STVAR-BTGARCH-M model in the DCC approach

Pair of Country	STVAR-BGARCH-M	STVAR-BTGARCH-M	LR Statistic	$p-$value
Devloped-Devloped combination				
US-UK*	–	-8283.05	–	–
US-HO	-8556.04	-8473.22	165.6278	(0.00)
US-JAP	-8589.44	-8500.39	178.0982	(0.00)
UK-HO	-8347.31	-8283.5	127.6268	(0.00)
UK-JAP	-8392.89	-8343.14	99.4946	(0.00)
HO-JAP	-8962.5	-8942.37	40.258	(0.00)
Emerging-Emerging combination				
BR-RUS	-10819.4	-10792.1	54.5786	(0.00)
BR-IND	-10276.7	-10232.3	88.8052	(0.00)
BR-CH	-10369.9	-10345.7	48.4606	(0.00)
RUS-IND	-10567.3	-10536.1	62.3468	(0.00)

Continued on next page

[2]in case of 3 pairs *viz.*, US-UK, US-CH, Hong Kong-India, convergence could not be achieved.

Table: 5.2 Continued from previous page

Pair of Country	STVAR-BGARCH-M	STVAR-BTGARCH-M	LR Statistic	$p-$value
RUS-CH	-10663.4	-10653	20.7754	(0.00)
IND-CH	-9991.1	-9976.3	29.5858	(0.00)
Devloped-Emerging combination				
US-BR	-8815.78	-8753.4	124.765	(0.00)
US-RUS	-9598.67	-9540.86	115.6208	(0.00)
US-IND	-9025.1	-8941.37	167.4624	(0.00)
US-CH*	–	–	–	
UK-BR	-8994.85	-8943	103.692	(0.00)
UK-RUS	-9278.27	-9226.24	104.0586	(0.00)
UK-IND	-8788.18	-8716.59	143.173	(0.00)
UK-CH	-8962.12	-8911.38	101.4668	(0.00)
HO-BR	-9898.97	-9862.54	72.8626	(0.00)
HO-RUS	-10212.2	-10181.8	60.829	(0.00)
HO-IND*	-9390.66	–	–	–
HO-CH	-9585.83	-9551.03	69.5994	(0.00)
JAP-BR	-9984.2	-9936.16	96.0706	(0.00)
JAP-RUS	-10294.2	-10268.6	51.2224	(0.00)
JAP-IND	-9586.6	-9542.92	87.3688	(0.00)
JAP-CH	-9728.12	-9701.46	53.3134	(0.00)

Note: $p-$values are given in parentheses. * implies those pairs where one of the two models can not computes as the convergence don't achieved.

Since the essential difference between the two proposed models - one in the preceding chapter and the other in the chapter - is in the approaches used[3] - the DCC and the BEKK - in studying risk-return relationship with due consideration to up and down market conditions and asymmetry in conditional variance, we have presented the maximum log-likelihood values for the two models in Table 5.2 to find which of the two approaches performs better for our data sets. Since the two models are not nested in their parameter spaces, no formal statistical test could be carried out. However, looking at these two

[3]There is another difference in that in case of BEKK approach, TVAR is the model for mean whereas in case of DCC approach the model is STVAR.

sets of values we can observe that the performance of the BEKK model is better for all pairs of stock markets in all the three i.e., D-D, E-E, and D-E combinations.

5.4 Conclusions

In this chapter, we have proposed the STVAR-BTGARCH-M model and used the DCC approach for H_t to estimate this model for all the 28 pairs of stock markets involving four developed economies and four important emerging economies called the BRIC group. As in the preceding chapter, in this chapter also, we have empirically found the importance of dependence between two stock markets in studying the risk-return relationship in bivariate set-up, and also the relevance and necessity of modelling consideration to market situations like up and down markets. To be more specific, we have found that all the three kinds of spillover effects - mean, variance, and 'BTGARCH-in-mean' - are significant, although in varying numbers, in the three combinations of stock markets considered. In case of mean spillover, we have found that one market affects the other; in case of variance spillover, both direct and indirect effects are significant for a number of pairs. We have also noted that the risk of one market affects the return of another market, and this holds for both the market conditions *viz.*, up and down, for a number of pairs of stock markets.

Chapter 6

Effects of Monetary Policy on Stock Returns Under Up and Down Markets: The Markov Switching Regression Model

6.1 Introduction

Stock market is an important channel of monetary policy that can be used to influence real economic activities. Real economic activities are affected by stock markets through a number of channels such as wealth effect of stock prices on consumption and economic growth. Hence, it has been of great interest to both the financial economists and macroeconomists to study whether monetary policy affects stock returns or not. A number of empirical studies have found that a change in monetary policy can change the future stock returns. For instance, using money aggregate data as a measures of monetary policy, Keran (1971), Homa and Jaffee (1971), and Hamburner and Kochin(1972) have shown that monetary policy has a significant role to predict stock returns. On the other hand, Cooper (1974), Pesando (1974), Rozeff (1974), and Rogalski and Vinso (1977) have shown that there is no significant role of changes in money in forecasting stock returns. Thus, on the basis of available empirical evidence till the late 1980's, it may be concluded that insofar as the existence of this particular relationship is concerned, it could be either way. However, this is at the same time intriguing. Hence a natural question that might arise is: Is the finding of (in)significant role of changes in money supply is due to some inadequacies in the modelling approach and assumptions as well as in the choice of the instruments for monetary policy?

Bernanke and Blinder, in their seminal paper in 1992, first used the Federal funds rate as a measure of monetary policy. Since then it has been widely used, and the relationship between monetary policy and stock return has been re-examined by using this interest rate instrument. Thorbecke (1997) and Patelis (1997) have shown that shift in monetary policy can help to predict stock returns. Conover *et al.* (1999) have found that foreign stock returns generally react both to local and US monetary policies.

Furthermore, cyclical variation, particularly bull and bear situations in stock market, is a widely reported phenomenon in every stock exchange. (see, in particular, Maheu and McCurdy (2000), Pagan and Sassounov (2003) and Lunde and Timmermann(2004))[1]. Chen (2007) raised the question: Does a monetary policy have different (asymmmetric) effects on stock returns in bull and bear markets? Based on monthly returns on the S&P 500 index, he found that monetary policy has larger effects on stock returns in bear markets. We also empirically examine this question from consideration to what we have called up and down market movements. As in Chen (2007), we have used a modified version of the Markov regime switching regression developed by Hamilton (1989) in two different perspectives. First, by applying the fixed transition probability (FTP) Markov switching model where the transition probabilities are fixed over time, and second, by allowing the switches between the two markets to depend on monetary policy, and thus making the model to be time-varying transition probability (TVTP) Markov regime switching regression, which is due to Diebold *et al.* (1994). In this study, we have also used different measures of monetary policy *viz.*, growth rate of money supply and discount rate.

The purpose of such a study is to empirically investigate if monetary policy has different effects on stock returns. To the best of our knowledge, such studies have not been carried out, following the two approaches mentioned above, for other developed stock markets and important emerging economies. We carry out a study similar to that of Chen (2007) for the 3 developed economies[2] (the US, the UK, Japan) and four emerging economies (Brazil, Russia, India and China) in this chapter. In Chapters 3, 4 and 5, we have considered regime switching with observed transition models such as threshold regression and smooth transition regression which identify the two states of the stock market by the average return of last k time points with data at daily level. In this chapter, we are, in fact, considering unobserved regime switching model, as in Chen (2007), where both the FTP and TVTP versions of the Markov regime switching model are being applied using data at monthly level[3].

[1]Some other important references are: Turner *et al.* (1989), Hamilton and Lin (1996), and Perez-Quiros and Timmermann (2000, 2001)

[2]Since the data on money supply for Hong Kong are not available on any website in public domain, this country was dropped from this study.

[3]In the previous three chapters, the analysis was done with daily level data and to that end, we defined the market

The format of the chapter is as follows. Section 6.2 presents the methodology used in this work. Data sets are stated in Section 6.3. Empirical analysis is carried out in Section 6.4. Concluding remarks are made in Section 6.5.

6.2 Methodology

In this section, we briefly describe the modified version of the Markov switching regression with fixed transition probability as well as with time-varying transition probability, where the modification is from consideration of including an instrument for monetary policy as an explanatory variable in the conditional mean model for r_t. We also mention about the tests to be carried out in order to conclude if the effects of monetary policy on stock returns are same from consideration to up and down market conditions.

6.2.1 Modified Markov switching regression with fixed transition probability model

The standard Markov switching model of stock returns for two states is as follows:

$$\varphi(B)r_t = \mu_{s_t} + \varepsilon_t, \qquad \varepsilon_t \sim iidN(0, \sigma^2_{s_t}) \tag{6.1}$$

where $\varphi(B) = 1 - B - B^2 - \ldots - B^p$ and B is the backward shift operator. μ_{s_t} and $\sigma^2_{s_t}$ are the state dependent mean and variance of r_t, respectively. The unobserved state variable, s_t, is a latent dummy variable which takes the value 0 and 1 for up and down markets, respectively. It is assumed to follow a two-state Markov process with fixed transition probability matrix: $P = \begin{bmatrix} p^{00} & 1-p^{11} \\ 1-p^{00} & p^{11} \end{bmatrix}$ where $p^{00} = P(s_t = 0|s_{t-1} = 0)$, $p^{11} = P(s_t = 1|s_{t-1} = 1)$. The functions of the transition probabilities are specified as $p^{00} = \frac{\exp(\theta_0)}{1+\exp(\theta_0)}$ and $p^{11} = \frac{\exp(\gamma_0)}{1+\exp(\gamma_0)}$. It may be noted that if the order of lag, p, is chosen as 0, then this model becomes the simple mean-variance Markov switching model (Hamilton (1990)).

To capture the effect of monetary policy on stock returns, we take the modified version of the Markov

movements as up and down. In this chapter, all the data sets are at monthly frequency since data for money supply and discount rate are not available at frequencies higher than monthly, and hence the two different market conditions can be stated as bull and bear, as done in Chen (2007), or up and down, as we have done earlier. We, however, continue to identify the market movements as up and down.

switching model, as proposed in Chen (2007). This model can be written as

$$r_t = \mu_{s_t} + \sum_{i=1}^{q} b_{s_t,i} x_{t-i} + \varepsilon_t, \qquad \varepsilon_t \sim iidN(0, \sigma_{s_t}^2) \tag{6.2}$$

where x_t is the variable representing monetary policy at time t. Clearly, the monetary policy is allowed to have different impacts on stock returns across the two different states. As noted in Chen (2007), this empirical approach is open ended in the sense that it may be found out that the monetary policy has no significant impact on stock returns in the up and down market conditions, or that it has similar/different significant effects in both the market conditions.

6.2.2 Modified Markov switching regression with time varying transition probability

In this model we assume that the transition probabilities vary with time. Also, we allow the probability of switching between the two states - up and down - to depend on monetary policy. The transition probability matrix is now represented as $P(t) = \begin{bmatrix} p_t^{00}(x_{t-1}) & 1 - p_t^{11}(x_{t-1}) \\ 1 - p_t^{00}(x_{t-1}) & p_t^{11}(x_{t-1}) \end{bmatrix}$ where $p_t^{ij}(x_{t-1}) = P(s_{t-1} = j | s_{t-1} = i, x_{t-l})$, $i, j = 0, 1$, and x_{t-l} is the monetary policy at time $t-1$.

It is obvious that the probability of a switch from one state to another is assumed to vary with the changes in the monetary policy over time.

The functions of the transition probabilities are then specified as

$$p_t^{00} x(t-1) = \frac{\exp(\theta_0 + \theta_1 x_{t-1})}{1 + \exp(\theta_0 + \theta_1 x_{t-1})} \tag{6.3}$$

and

$$p_t^{11} x(t-1) = \frac{\exp(\gamma_0 + \gamma_1 x_{t-1})}{1 + \exp(\gamma_0 + \gamma_1 x_{t-1}))}. \tag{6.4}$$

The first-order derivatives of the transition probabilities with respect to x_{t-1} are given as:
$\frac{\partial p_t^{00}}{\partial x_{t-l}} = \theta_1 p_t^{00}(1 - p_t^{00})$ and $\frac{\partial p_t^{11}}{\partial x_{t-l}} = \gamma_1 p_t^{11}(1 - p_t^{11})$.

Since $1 \geq p_t^{00}, p_t^{11} \geq 0$, the signs of $\frac{\partial p_t^{00}}{\partial x_{t-l}}$ and $\frac{\partial p_t^{11}}{\partial x_{t-l}}$ are determined by the signs of θ_1 and γ_1, respectively. Thus, the estimates of θ_1 and γ_1 indicate how monetary policy affects the switching between up and down markets.

6.3 Data

The data sets required for this study are the 7 stock indices at monthly frequency of seven countries, *viz.*, S&P 500, (the US), FTSE (the UK), NIKKEI 225 (Japan), BOVESPA (Brazil), MICEX (Russia), SENSEX (India), SSE COMPOSITE (China), as well as money supply (M3 for India, M4 for the UK and M2 for the others) and discount rate. Money supply and discount rate have been taken as instruments of monetary policy. Further, the stock indices have been taken as nominal and real (adjusted with CPI inflation) with the purpose of checking to what extent the findings (on whether monetary policy has asymmetric/different effects on stock returns) are robust. Time series data of these variables have been downloaded from the websites of Federal Economic Research St. Louis (http://research.stlouisfed.org/fred2/), Reserve Bank of India (http://www.rbi.org.in/home.aspx), Yahoo Finance (http://finance.yahoo.com/), Bombay Stock Exchange (http://www.bseindia.com/). The period of monthly observations for this study is January 2000 to December 2012. The important properties of these time series have already been discussed in Section (2.4) of Chapter 2. All the time series have been found to be nonstationary, and the stationary series obtained for these variables: nominal returns, real returns, growth rate of money supply (GMS) and change in discount rate (CDR).

6.4 Empirical Results

6.4.1 Findings on the MS-FTP model

We first report the results of the modified Markov switching regression with fixed transition probabilities (MS-FTP), as given in Section 6.2.1. Estimates of all the relevant parameters of this model for the 7 stock markets are given in Table 6.1. The lag of the explanatory variable *viz.*, growth rate of money supply (GMS) or change in discount rate (CDR) has been selected by the SIC. In most of the cases, we have found that a single lag of the explanatory variable is adequate. The first two rows of the table present the estimates of the parameters, θ_0, and γ_0 . An important point to note for these estimates is that it is notoriously difficult to obtain their precise standard errors, as stated in Bates and Watts (1998), and Frances and van Dijk (2000).

Now, as regards the 4 parameters of means and variances for the two states, μ_0, μ_1, σ_0, σ_1, we note that in all the 7 markets, the estimate $\hat{\mu}_0$ is positive and significant while $\hat{\mu}_1$ is negative and significant - both in all the four cases (i.e., nominal and real returns with GMS/CDR as the instrument of monetary policy). Further, the estimates of σ_0^2, σ_1^2 are significant, and obviously positive, for all the cases and for all the 7 countries.It is also noted that $\hat{\sigma}_0^2$ is smaller than $\hat{\sigma}_1^2$.

In the regime switching model of stock returns, different market conditions *viz.*, up and down markets, are identified by 'high returns with low variance' and 'low returns with high variance', respectively. In all the models for both nominal and real returns involving the 7 countries, we find that high return is associated with low variance as well as low return with high variance. Thus, the two market conditions are clearly identified for all the seven countries, irrespective of their developmental status - developed or emerging.Given these findings we can, therefore, identify the state 0 to be the up market and the state 1 to be the down markets.

Thus the coefficient $b_{0,i}$ captures the impact of change in monetary policy in the up market whereas $b_{1,i}$ captures the impact of the same in the down market.

Table 6.1: Estimates of the parameters of the MS-FTP model and the values of the Wald test statistic

	The US				**The UK**				**Japan**			
	Nominal Return		Real Return		Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	-0.7241	-0.5081	-0.6730	-0.4104	-0.6773	-0.1357	-0.3264	-0.3110	-0.2584	-0.1467	-0.2814	-0.1417
γ_0	1.0484	0.3885	0.4594	0.4356	0.1319	0.5581	0.2615	0.5651	0.6951	0.7924	0.5819	0.7421
μ_1	1.7310	2.6178	2.2569	2.3915	3.0858	2.5896	2.9459	2.7217	3.4491	3.4370	3.7337	3.5665
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_2	-6.8315	-5.1056	-5.2397	-5.3259	-3.1747	-4.6017	-3.2619	-4.1062	-6.6190	-6.6301	-6.2133	-6.4231
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
b_{11}	0.1397	0.8017	-0.1633	1.0046	-0.1346	3.4474	-0.1277	1.2401	-0.4759	6.6101	-0.8452	4.7143
	(0.79)	(0.60)	(0.76)	(0.47)	(0.07)	(0.02)	(0.07)	(0.35)	(0.63)	(0.26)	(0.40)	(0.42)
b_{12}						-8.1730		-5.9595		-8.6622		-9.3602
						(0.00)		(0.00)		(0.09)		(0.06)
b_{21}	-0.6953	4.0788	-1.0861	4.0412	-1.1104	11.4376	-1.1443	3.8612	-0.3046	15.0099	-0.6311	13.4564
	(0.50)	(0.01)	(0.20)	(0.01)	(0.02)	(0.01)	(0.01)	(0.25)	(0.82)	(0.10)	(0.61)	(0.14)
b_{22}						-5.7202		-1.1820		-8.5537		-8.7920
						(0.07)		(0.61)		(0.55)		(0.53)
σ_1	7.9041	6.0656	6.8437	6.4027	3.6075	4.1037	3.5056	3.2466	9.5213	9.1949	8.8477	8.7870
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_2	8.4368	9.5069	9.4551	8.9932	9.4750	9.1908	9.3352	9.9210	16.1471	15.2961	16.3726	15.4067
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
p^{00}	0.33	0.38	0.34	0.40	0.34	0.47	0.42	0.42	0.44	0.46	0.43	0.46
p^{11}	0.74	0.60	0.61	0.61	0.53	0.64	0.57	0.64	0.67	0.69	0.64	0.68
W	0.816	3.1574	1.4107	2.9221	4.0255	14.4445	5.3966	9.4707	0.0206	0.5938	0.036	0.6634
	(0.37)	(0.08)	(0.23)	(0.09)	(0.04)	(0.00)	(0.02)	(0.01)	(0.89)	(0.74)	(0.85)	(0.72)
MLL	-385.94	-384.15	-387.54	-385.13	-367.66	-361.84	-366.68	-360.99	-421.18	-414.91	-419.95	-413.76

	Brazil				**Russia**			
	Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	0.1204	0.1106	0.0584	0.1257	-0.2840	-0.1817	-0.4136	-0.1491
γ_0	0.4912	0.6243	0.3360	0.4984	0.2685	0.3625	0.2242	0.4430
μ_1	7.7281	7.6948	7.4247	7.4043	6.3798	8.3086	5.4876	7.2527
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_2	-3.5538	-4.3767	-3.8376	-4.6228	-11.6663	-7.5055	-12.5127	-8.5335

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Table: 6.1 Continued from previous page

	Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
b_{11}	0.0631	-0.4646	0.0803	-0.3427	0.4035	-1.4815	0.3800	-1.5009
	(0.82)	(0.32)	(0.77)	(0.49)	(0.01)	(0.00)	(0.01)	(0.00)
b_{12}		-0.3418		-0.5738	0.3204		0.3015	
		(0.62)		(0.41)	(0.03)		(0.04)	
b_{21}	-0.7689	-0.2438	-0.7746	-0.0650	0.8335	-2.8261	0.7855	-2.8229
	(0.01)	(0.79)	(0.01)	(0.94)	(0.00)	(0.00)	(0.00)	(0.00)
b_{22}		-1.9713		-2.1778	0.6435		0.6234	
		(0.00)		(0.00)	(0.01)		(0.01)	
σ_1	10.7580	10.4850	9.9881	9.7331	22.8912	21.2865	22.3785	20.7473
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_2	24.8658	23.2194	25.3685	23.5796	41.5406	47.1896	42.1915	47.2047
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
p^{00}	0.53	0.53	0.51	0.53	0.43	0.45	0.40	0.46
p^{11}	0.62	0.65	0.58	0.62	0.57	0.59	0.56	0.61
W	4.8659	3.3977	4.9099	3.2124	3.6408	2.2771	3.6782	2.1937
	(0.03)	(0.18)	(0.03)	(0.20)	(0.16)	(0.13)	(0.16)	(0.14)
MLL	-450.88	-443.58	-451.20	-443.27	-491.65	-499.97	-490.82	-498.72

	India				**China**			
	Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	-0.1093	-0.1694	-0.2752	-0.4599	-0.1293	-0.0087	-0.1933	0.0030
γ_0	-0.0022	-0.0306	-0.0465	-0.1453	0.5763	0.8352	0.4766	0.7490
μ_1	7.2131	7.6363	6.5809	6.6918	2.8650	5.3948	3.0718	5.3736
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_2	-3.0810	-4.3420	-3.5163	-5.4171	-10.2621	-8.0078	-10.0095	-8.0070
	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
b_{11}	0.3089	-2.7978	0.0069	-2.7665	2.9456	-6.8159	2.6252	5.1089
	(0.43)	(0.00)	(0.99)	(0.01)	(0.00)	(0.05)	(0.00)	(0.21)
b_{12}								
b_{21}	-1.0707	4.5920	-1.7065	4.0873	2.4843	-5.5594	2.2344	10.2273
	(0.16)	(0.15)	(0.06)	(0.16)	(0.00)	(0.25)	(0.00)	(0.04)
b_{22}								
σ_1	11.2054	11.1621	13.2477	12.7318	16.9991	19.7830	16.5826	19.5484
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_2	26.6347	27.1095	25.9529	27.9198	32.6117	29.6472	31.4798	28.9431
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
p^{00}	0.47	0.46	0.43	0.39	0.47	0.50	0.45	0.50
p^{11}	0.50	0.49	0.49	0.46	0.64	0.70	0.62	0.68
W	3.4037	4.9896	4.0689	4.7413	0.3439	0.0463	0.266	0.7223
	(0.07)	(0.03)	(0.04)	(0.03)	(0.56)	(0.83)	(0.61)	(0.40)
MLL	-458.23	-458.35	-460.43	-461.44	-477.55	-478.56	-475.54	-477.08

Note: $p-$values are given in parentheses.

From the second column of Table 6.1, it is clear that, in case of the USA, a contractionary monetary policy decreases the nominal return in up market whereas it increases the return in down market condition, although it is not so powerful an instrument to control stock returns since estimated coefficients *viz.*, 0.1379 (for $\hat{b}_{0,1}$) and -0.6953 (for $\hat{b}_{0,1}$) are statistically not significant in both the market conditions. But in case of real returns, the situation is quite different. Here it is found that in the up market also and hence in the two market conditions, the real stock return increases (decreases) as the growth rate of money supply decreases (increases) since both the coefficients are found to be negative. The possible explanations for this lies in the fact that real returns are adjusted for CPI inflation. Once again, it needs to be mentioned that these conclusions are not very strong as the coefficients are statistically insignificant. In case of the UK and Japan, we observe that any change in money supply growth changes the stock returns in the opposite direction, no matter whether the stock market is in up or down situation. But the effect is much higher in the down market than in the up market. As for instance, This is evident from the facts that in case of the UK, the estimates of $b_{0,1}$ and $b_{1,1}$ for nominal returns are -0.1346 and -1.1104 with $p-$values 0.07 and 0.02, respectively. The conclusion is the same for real returns as well.

To check if the effects of this instrument (GMS) on the two market conditions are significantly different, we have computed the Wald test statistic (W), the values of which are also given in Table 6.1. From these values, it is evident that in case of the USA and Japan, the 'null hypothesis of equal effects' is not rejected for both nominal and real returns while for the UK it is rejected at 5% level of significance for both the return series. Thus we note that the conclusion on the role of GMS on returns (nominal and real) is quite contrast in nature between the UK on the one hand and the USA and Japan on the other.

Now, in so far as the findings on the effects of GMS on returns on stock indices for the four emerging economies are concerned, the results are somewhat different. In case of Russia and China, we find that GMS has significant positive impact on both nominal and real stock returns both in up and down markets. This means that under contractionary monetary policy, the returns decrease for both market movements for both the countries. But in both cases, the Wald test shows that the 'null hypothesis of equal effects' in up and down markets cannot be rejected.

As regards each of the remaining 2 emerging economies *viz.*, Brazil and India, we find that the estimate of $b_{0,1}$ is positive while that for $b_{1,1}$ is negative. However, the coefficients for nominal and real returns in the down markets are significant for Brazil; but it is significant only for real return in case of India. For up market, the coefficients for real and nominal returns are insignificant for both of them. However, the finding on the null hypothesis is quite interesting since in both the countries the 'null hypothesis of equal effects' is rejected. Thus, we find that in this group of four emerging economies, the conclusions in regard to the sign and significance of the coefficients as well as acceptance/rejection of the null hypothesis, are different between the two pairs *viz.*, Russia and China, and Brazil and India, while within the two members of any pair, the findings are quite similar. It is also interesting to note that these conclusions on India and Brazil are quite similar to those of the USA and Japan although the former pair of countries belongs to BRIC group while the latter pair comprises two most developed economies of the world.

It may be noted that we have found that there is a negative relationship between money supply growth and stock returns for some countries including India. This is not very clear why it should be so from the point of view of economic logic. In fact, one can argue that if the money supply growth increases due to increase in foreign capital inflow (especially to stock market) then generally return on stock market should increase. Since the results suggests otherwise we try to give some explanations for such findings from Keynesian point of view. In this view, the economists argue that change in the money supply will affect the stock prices only if the change in the money supply alters expectations about future monetary policy. According to them, a positive money supply shock will lead people to anticipate tightening monetary policy in the future. They bid for funds in anticipation of tightening of money supply in the future, which will drive up the current rate of interest. As the interest rate goes up, the discount rates go up as well and the present value of future earnings falls. Stock prices consequently decline. Furthermore, they argue that economic activities decline as a result of increase in interest rates, which further depresses stock prices (Sellin, 2001).

Now we discuss the results when change in discount rate (CDR) is taken to be the instrument for monetary policy. The findings are quite mixed for both the developed and emerging groups for this instrument. There is broadly no similarities even within the members of developed and emerging countries. In terms of statistical significance of the coefficients, the following have been observed. For the USA, only the coefficient for down market is significant for both nominal and real returns, and its sign is positive. In case of the UK, the coefficient is significant for up market for both nominal and real returns, but significant only for nominal returns in down market. None of the coefficients are found to be significant in any of the market conditions for Japan.

In the emerging group of countries, the only coefficient found to be significant (negative) for Brazil is for the down market condition for both nominal and real returns. For India, it is only in up market that the coefficient (negative) is significant for both nominal and real returns. Both the coefficients (all negative) in up and down markets are significant for both nominal and real returns in case of Russia. Finally, in China, for nominal returns, the coefficient in up market is significant (negative) while for real returns, the coefficient in down market is significant (positive). It is thus noted that from consideration of significant role of CDR in stock returns, most of these coefficients are negative across both developed and emerging economies. This implies that often these two variables are found to move in opposite directions. Finally, in terms of performance by the Wald test, the 'null hypothesis of equal effects' is rejected for the USA (at 10% level of significance), the UK (at 1% level), and India (5% level).

6.4.2 Findings on the MS-TVTP model

In the case of time varying Markov switching regression (MS-TVTP), the transition probability is a function of the instrument of monetary policy. This model investigates a different question *viz.,* if a change in monetary policy instrument can change the probability of switching from one state to another in a stock market. In other words, the issue is whether monetary policy is informationally relevant for the determination of the states of the markets. As we have already mentioned in Section 6.2.2, the signs of $\frac{\partial p_t^{00}}{\partial x_{t-l}}$ and $\frac{\partial p_t^{11}}{\partial x_{t-l}}$ are determined by the signs of θ_1 and γ_1, respectively as $1 \geq p_t^{00}, p_t^{11} \geq 0$.

Table 6.2: Estimates of the parameters of the MS-TVTP model

	The US				The UK				Japan			
	Nominal Return		Real Return		Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	-0.9997	-0.444	-0.7379	-0.2343	-0.6154	-0.8296	-0.7409	-0.5586	-0.3286	-0.2538	-0.2779	-0.2212
γ_0	1.0961	1.1596	1.2986	1.2471	0.1856	0.1779	-0.241	0.2871	0.7837	0.7314	0.7223	0.662
	(0.20)	(0.14)	(0.18)	(0.11)	(0.73)	(0.74)	(0.74)	(0.62)	(0.23)	(0.25)	(0.27)	(0.32)
θ_1	0.6271	1.29	0.5219	1.5335	-0.1582	-1.3408	0.1685	-1.8913	0.1401	-8.7025	0.0469	-14.082
	(0.84)	(0.89)	(0.87)	(0.83)	(0.88)	(0.82)	(0.76)	(0.71)	(0.93)	(0.89)	(0.97)	(0.70)
γ_1	-0.0293	1.2735	-0.2359	1.4744	0.0324	0.0035	0.6852	0.897	-0.5819	5.1152	-0.5297	4.7796
	(0.98)	(0.74)	(0.84)	(0.70)	(0.87)	(1.00)	(0.36)	(0.85)	(0.69)	(0.75)	(0.72)	(0.71)
μ_0	1.7762	1.7352	1.4802	1.451	2.8777	2.8798	2.5878	2.7157	3.325	3.3072	3.4802	3.4765
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_1	-7.3411	-7.4862	-7.7599	-7.8741	-4.2086	-4.2006	-4.4945	-4.3219	-6.7943	-6.8122	-6.561	-6.5567
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_0	7.9647	8.0879	8.4577	8.545	4.0061	4.0065	4.0573	3.9014	9.6648	9.7534	9.2149	9.2667
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_1	8.4765	8.2013	7.375	7.1084	9.9913	10.0161	10.0735	9.8817	15.922	15.9226	15.9929	16.0141
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLL	-386.33	-386.29	-387.45	-387.41	-371.86	-371.86	-371.61	-370.84	-421.21	-421.15	-420.27	-420.14

	Brazil				Russia			
	Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	0.0794	0.0996	0.0603	0.0206	-0.0593	-0.3522	-0.1057	-0.3438
γ_0	0.9395	0.5609	0.8501	0.3075	(0.44)	0.2262	0.5307	0.3042
θ_1	0.0754	-0.3249	0.054	-0.5037	-0.0977	-0.7572	-0.079	-0.9077
γ_1	-0.2454	0.1728	-0.2595	-0.4114	-(0.09)	0.1349	-0.0961	0.1146
μ_0	7.8297	7.7969	7.4995	7.5437	8.8413	8.7287	7.6921	7.6252
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_1	-4.5245	-4.5526	-4.8588	-4.819	-(7.07)	-7.2061	-8.2241	-8.3132
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_0	10.6218	10.7463	9.9999	9.8556	24.4961	24.9272	24.2828	24.5607
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_1	26.7497	26.6838	27.1645	27.2719	(50.68)	50.4116	50.4211	50.2105
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLL	-453.99	-454.1	-454.395	-454.438	-(508.36)	-508.451	-507.224	-507.335

	India				China			
	Nominal Return		Real Return		Nominal Return		Real Return	
	GMS	CDR	GMS	CDR	GMS	CDR	GMS	CDR
θ_0	-0.1022	-0.0679	-0.5433	-0.3485	-0.53	-0.0266	-0.5545	-0.0802
γ_0	-0.6919	-0.0311	-0.7057	-0.0954	0.354	0.7474	0.2264	0.6795
θ_1	-0.0237	2.322	0.1042	1.2282	0.3539	-13.4547	0.3336	-15.8438
γ_1	0.6137	0.261	0.47	1.6643	0.3411	-3.6482	0.4127	-3.697
μ_0	7.5896	7.5413	6.6697	6.6141	5.4075	5.4106	5.3411	5.3302
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
μ_1	-4.4984	-4.5457	-5.5621	-5.6182	-7.7203	-7.7338	-7.705	-7.7418
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_0	11.3816	11.6439	12.9404	13.1457	20.4382	20.4085	19.4246	19.4325
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
σ_1	27.3075	27.1075	27.8081	27.6953	30.6438	30.4577	30.0395	29.7911
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
MLL	-459.592	-459.773	-462.317	-462.438	-480.915	-481.026	-477.926	-478.034

Note: $p-$values are given in parentheses. * implies those pairs where one of the two models can not computes as the convergence don't achieved.

Thus the estimates of θ_1 and γ_1 indicate how monetary policy can influence a stock market such that in switches from one regime to the other. For instance, a positive $\hat{\theta}_1$ suggests that an increase in money supply growth (GMS) makes this stock market more likely to stay in the up market, whereas a negative $\hat{\theta}_1$ implies that an increase in GMS can switch the stock market from up market state to down market state.

Table 6.2 presents the results of the MS-TVTP model where the transition probability has been assumed to be a function of the lag values of one of the two instruments of monetary policy mentioned earlier, i.e., GMS and CDR. This model has been run separately for each of these two instruments. The first observation from this table is that the estimate of μ_0 is positive for each of the seven countries and the estimate of μ_1 is negative for each of te seven countries. Estimates of σ_0 and σ_1 are obviously positive and $\hat{\sigma}_0$ is always greater that $\hat{\sigma}_1$. These findings are exactly similar in case of the MS-FTP model. As regards the other parameters, it is found that in case of the USA, $\hat{\theta}_1 > 0$ for all 4 regressions (two returns series *viz.*, nominal and real, and two instruments of monetary policy *viz.*, GMS and CDR). But $\hat{\gamma}_1 < 0$ in both nominal and real returns where GMS is taken as a monetary policy instrument, and $\hat{\gamma}_1 > 0$ in two cases of CDR. This implies that an increase in money supply growth increases the probability to stay in up market, whereas it decreases the probability to stay in down market. But in those cases where CDR is taken as monetary policy instrument, an increase in CDR increases the probability of staying in the same regime. But in case of the UK, the results are quite different compared to the USA market. Here, an increase in CDR decreases the probability of the stock market staying in up market situation - both for nominal and real returns, but this also increases the probability of staying in down market situation as $\hat{\theta}_1 < 0$ and $\hat{\gamma}_1 > 0$. In case of Japan, the results are similar as in the USA when GMS is the instrument, but when CDR is taken as the policy instrument, the results are similar to those for the UK market.

In case of the four emerging economies, there are not many similarities in the findings. In case of Russia, an increase in GMS decreases the probability of the stock market remaining in the same state. This finding is quite opposite in nature in case of China where an increase in GMS increases the probability of the stock market staying in the same state. With CDR as the instrument for monetary policy, the conclusions are once again opposite in nature insofar as the probability of the concerned stock market (Russia or China) remaining in the same state is concerned.

6.5 Conclusions

In this chapter, we have examined if the effects of monetary policy on stock market movements like up and down markets are different. This has been done with data from three developed economies and four emerging economies and applying the MS-FTP and MS-TVTP models. In case of the MS-TVTP, we have taken two instruments of monetary policy *viz.*, money supply and discount rate.

Now, as regards the four parameters of means and variances for the two states, μ_0, μ_1, σ_0, σ_1, we note that in all the seven markets, $\hat{\mu}_0$ is positive and significant while $\hat{\mu}_1$ is negative and significant in all the four cases (i.e., nominal and real returns with GMS/CDR as the instrument of monetary policy). Also, the estimate of mean of the first state ($\hat{\mu}_0$) is always greater than the estimate of mean of the second state, $\hat{\mu}_1$. Further, the estimates of σ_0^2 , σ_1^2 are significant, and obviously positive, for all the cases and for all the 7 countries. It is also noted that $\hat{\sigma}_0^2$ is smaller than $\hat{\sigma}_1^2$. These findings hold for both the MS-FTP and MS-TVTP models.

Thus we find that in all the models for both nominal and real returns involving the 7 countries, high return is associated with low variance as well as low return with high variance. Hence, the two market conditions are clearly identified for all the seven countries, irrespective of their developmental status - developed or emerging. Given these findings we can, therefore, identify the state 0 to be the up market and the state 1 to be the down markets.

As regards the effects of the monetary policy on stock returns in terms of the MS-FTP model, we note that in case of the USA, a contractionary monetary policy decreases the nominal returns in up market whereas it increases the nominal returns in down market condition, although it is not so powerful an instrument to control stock returns - both nominal and real. The findings on Japan are almost the same as in case of the USA i.e., lags of the instrument GMS are not significant for both nominal and real returns. The lag effects of GMS on returns for the UK, on the other hand, are in sharp contrast to those of the USA and Japan. Here lag values are significant for both the nominal and real returns. In terms of statistical significance, we find that in case of GMS, the 'null hypothesis of equal effects' is not rejected for the USA and Japan for both nominal and real returns while for the UK, it is rejected at 5% level of significance for both the return series.

Our findings on the effect of CDR on stock returns involving all the countries is that mostly the coefficients are insignificant. And in those cases where it is significant, the coefficients are mostly negative. In terms of the 'null hypothesis of equal effects', the Wald test suggests that only for the UK, the US and India, the null hypothesis is rejected for both nominal and real returns.

Finally, the findings in terms of the MS-TVTP model is that the effects of GMS and CDR are quite different between the US and the UK. In case of the US, an increase in GMS increases the probability to stay in up market whereas it decreases the probability to stay in down market; if CDR is the instrument, an increase in the value of CDR increases the probability of staying in the same market. But in case of the UK, these results are quite different from those of the USA. The findings in case of emerging economies is that there are not many similarities among the four countries. The main observation is that in case of Russia, an increase in GMS decreases the probability of the stock market remaining in the same state. This is quite opposite in case of China. With CDR as the instrument of monetary policy, the conclusions are once again opposite in nature between China and Russia.

Chapter 7

Conclusions and Future Ideas

7.1 Introduction

The focus of this thesis is to study the risk-return relationship at both univariate and multivariate levels with the special modelling consideration to two different market conditions *viz.*, up and down markets. The idea of incorporating the two market conditions in the model stems from the fact that the effect of risk is likely to be different in the two market conditions. The modelling framework also allows for the expected return to be directly affected by risk, which is indeed known as the 'volatility-in-mean' framework. Further in the proposed models, the conditional variance-covariance matrix has been taken to be asymmetric in nature. In this framework, we have proposed the TAR-EGARCH-M model for returns at the univariate level.

Extending this model, in a multivariate set-up, we have next proposed what has been called as the TVAR-BTGARCH-M and STVAR-BTGARCH-M models. The distinct advantage of studying returns model at multivariate level is that such models incorporate different kinds of spillovers effects across the stock markets concerned. We have studied this model using both the approaches - the BEKK (due to Baba *et al.*, (1990)) and the dynamic conditional correlation (DCC) methods.

Finally, we have empirically investigated whether monetary policy has different effects on the stock market under up and down market situations. Following Chen (2007), the (unobserved) regime switching model called the Markov switching regression model where the switch over from one state to another is influenced by the instruments of monetary policy, has been applied to identify the two different states of returns for each stock market separately. Both the variants of this model, *viz.*, the Markov switching regression with fixed transition probability as well as with time-varying transition probability, have been used in this study.

This study has been carried out with the returns on two broad categories of stock markets depending on there development status, called the developed economies and important emerging economies. Four stock indices from each of these two categories have been taken for this study. These are: S&P 500 (the US), FTSE ALL (the UK) Hang Seng (Hong Kong), NIKKEI 225(Japan), BOVESPA (Brazil), MICEX (Russia), SENSEX (India) and SSE COMPOSITE (China). The span of the data sets for both daily and monthly frequencies are January 2000 - December 2012.

The last chapter is organised as follows. A summary of the major findings of the entire work is presented in Section 7.2, and the last section i.e., Section 7.3 presents a few ideas for further work in this area.

7.2 Major Findings

In case of risk-return relationship under univariate analysis of stock returns at daily frequency, we have proposed a modelling framework where the model considers two different stock market situations, called the up and down markets, and where the risk directly affects the expected return through the specification of the conditional variance in the model for conditional mean return. The risk aversion parameter is taken to be different so that it can be investigated if risk responds differently in the two market situations. The specification of the conditional variance has been taken to be the EGARCH model which takes into account the leverage effect i.e., the asymmetric behaviour of return shocks on conditional variance. The two models capturing this feature, designated as the TAR-EGARCH-M and STAR-EGARCH-M models, differ only in respect of the fact that the logistic transition function is considered for smooth transition from one regime to the other in case of the latter model.

The empirical findings are overwhelmingly in favour of the proposed models i.e., the TAR-EGARCH-M and STAR-EGARCH-M models. It is found that the two regimes for mean returns referred to as up and down markets, are statistically valid for all the eight return series. Further and more importantly, risk in terms of time-varying conditional variance is found to respond ‘asymmetrically’ in the two market conditions in the sense that the risk aversion parameter is positive in case of down market and negative for up market. These empirical findings thus give support to the observations made by Fabozzi and Francis (1977) and Kim and Zumwalt (1979) that investors require a premium for taking downside risk and pay a premium for upside variation. Finally, it is also observed that modelling consideration to stock market conditions through the introduction of regimes yields statistically a better model since the AR-EGARCH-M model is found to be rejected, by the likelihood ratio test, in favour of the proposed TAR-EGARCH-M model for all stock markets except that of Japan.

Next we have generalised the model of the preceding chapter i.e., the TAR-EGARCH-M model for stock returns at univariate level, to bivariate set-up where returns on two stock markets are modelled together. This helps in capturing the spillover effects of mean and volatility of the two stock markets leading to a better risk-return relationship in bivariate set-up. To that end, we have proposed a model which is called as the TVAR-BTGARCH-M model where asymmetry in conditional variance and different effects of the two market conditions, up and down, on conditional mean have been incorporated in case of returns on two stock markets. Unlike the univariate model considered for the risk-return relationship, the asymmetry in conditional variance has been considered in terms of threshold GARCH model. Obviously, the consideration to'volatility-in-mean' component in the model allows for the risk to affect the conditional mean directly. Also, studying the risk-return relationship involving two return series enables that the spillover effects of one market on the other in terms of conditional mean, conditional variance as well as 'volatility-in-mean' component, are also taken into the modelling framework. There are in all 28 pairs of countries - made out of 4 developed and 4 emerging (BRIC) countries - where this model has been applied. These pairs have been categorised into 3 combinations *viz.* developed-developed (D-D), emerging-emerging (E-E) and developed-emerging (D-E). Along with the TVAR-BTGARCH-M model we have also estimated 4 other models *viz.*, the VAR-BGARCH, VAR-BGARCH-M, VAR-BTGARCH-M, TVAR-BGARCH-M models so as to be able to empirically investigate the usefulness and efficacy of the proposed model. It is to be noted that in case of GARCH or similar other volatility models in multivariate case, there are basically two different models for the conditional variance-covariance matrix, and accordingly the two approaches are called the BEKK and the dynamic conditional correlation (DCC) approaches. We first summarise the findings on the models by the BEKK approach.

The first major finding is that in many cases the parameters in the conditional mean part of the model are significant across the two market conditions, and that these are significantly different in a number of pairs. The findings in the 3 combinations of countries are more or less the same. There are a few cases where the market movements are not found to be significant and/or same. The symmetric component of volatility was found to be significant in all 28 combinations, as expected. The well-known fact of asymmetry in stock returns, which is often due to leverage effect, was found to be overwhelmingly present in this study.

Insofar as the spillover effects are concerned, all the 3 kinds of spillovers were found to be significant in many of the 28 pairs, although the respective numbers are not the same. The incidence of one market affecting the other in respect of one or both market conditions is found to be quite prevalent. There are only a few pairs where these spillover effects were found to be absent. On the other hand, these effects are found to be significant in both market movements for a few pairs. Across the 3 combinations, it is found that in the D-E combination the spillover effect from developed to emerging has occurred more often than it is in the reverse direction. The volatility as well as cross volatility spillovers are found to be very important in this model. In fact, both in terms of direct and indirect spillovers in variance, the findings are very strong in all the 3 combinations although in case of E-E combination, there are pairs where one of the direct and indirect effects is found to be absent.

In respect the 'BTGARCH-in-mean' effect we find that the spillover of direct/indirect risk of one market on the mean of the other market in respect of the two market conditions is quite prevalent although it is insignificant in a few cases as well, especially in D-E combination. It is quite natural that the risk of emerging economies would not have significant effects on the up and down market conditions of a developed economy as often as the effects in the reverse direction happens. In fact this is what has been observed as well. On the whole, it is found that different kinds of spillover effects, that too having reference of up and down market movements, are extremely important in modelling returns of two countries together in a unified framework.

Finally, it is noted that the log-likelihood value is maximum for the proposed model in comparison to the other four restricted models. Although the difference in the maximized log-likelihood value is not significant in a few cases, the importance of the model from statistical consideration is established for most of the pairs. This means that the modelling issues considered in this model *viz.*, up and down market movements, asymmetric variance and direct effect of risk on conditional mean are indeed very important in studying the risk-return relationship in bivariate set-up.

In the next work, we have essentially the same model with only one minor modelling difference *viz.*, instead of TVAR, we have taken the conditional mean model to be the smooth transition VAR. But, the main difference lies in the fact that we have now used the DCC approach for the conditional variance-covariance matrix. The major findings on the proposed model i.e., STVAR-BTGARCH-M model, under the DCC approach are stated below. As in the preceding model, we have found the importance of dependences between any two stock markets in studying the risk-return relationship in the bivariate set-up for both up and down markets. To be more specific, we have found that all the three kinds of spillover effects - mean, variance, and 'BTGARCH-in-mean' - are significant, although in varying numbers, in the three combinations of stock markets considered. In case of mean spillover, we have found that one market affects the other; in case of variance spillover, both direct and indirect effects are significant in a number of pairs. We have also noted that the risk of one market affects the mean return of another market and this holds for both the market movements *viz.*, up and down, for a number of pairs of stock markets.

In the last study, we have examined if the effects of monetary policy on stock market movements like up and down markets are different. This has been done with monthly level data from three developed economies and four emerging economies applying the Markov switching regression with fixed transition probability (MS-FTP) and the Markov switching regression with time-varying transition probability (MS-TVTP) models. In case of these two models, we have taken two instruments for monetary policy *viz.*, growth rate of money supply (GMS) and change in discount rate (CDR). The major findings on these two models are stated below.

As regards the four parameters of mean and variance for the two states, we have found that in all the seven markets, the estimate of mean is positive and significant for the first state while it is negative and significant for the second state. Also, the mean of the first state is found to be always greater than the mean of the second state. Further, the estimate of the variance of the first state has been found to be smaller than that of the second state. These findings hold for both the MS-FTP and MS-TVTP models.

Thus it is found that high return is associated with low variance as well as low return with high variance. Hence, the two market conditions are clearly identified for all the seven countries, irrespective of their developmental status - developed or emerging. Given these findings we can, therefore, identify the state 0 to be the up market and the state 1 to be the down market.

As regards the effects of the monetary policy on stock returns in terms of the MS-FTP model, we note that in case of the USA, a contractionary monetary policy decreases the nominal return in up market whereas it increases the return in down market condition, although it is not so powerful an instrument to control stock returns - both nominal and real. The findings on Japan are almost the same as in the USA i.e., lags of the instrument GMS are not significant for both the nominal and real returns. The lag effects of GMS on returns in case of the UK, on the other hand, are in sharp contrast to those of the USA and Japan. Here lag values are significant for both the nominal and real returns. In terms of statistical significance, we find that in case of GMS, the 'null hypothesis of equal effects' is not rejected for the USA and Japan for both nominal and real returns while for the UK it is rejected at 5% level of significance for both the returns series.

Our findings on the effect of CDR on stock returns involving all the countries are that mostly the coefficients are insignificant. And in those cases where it is significant, the coefficients are mostly negative. In terms of the 'null hypothesis of equal effects', the Wald test suggests that only for the UK, the US and India, the null hypothesis is rejected for both nominal and real returns.

Finally, the findings in terms of the MS-TVTP model is that the effects of GMS and CDR are quite different between the US and the UK. In case of US, an increase in GMS increases the probability to stay in up market whereas it decreases the probability to stay in down market; if CDR is the instrument, an increase in the value of CDR, increases the probability of staying in the same market. But in case of the UK, these results are quite different from those of the USA. The findings in case of emerging economies is that there are not many similarities among the four countries. The main observation is that in case of Russia, an increase in GMS decreases the probability of the stock market remaining in the same state. This is quite opposite in case of China. With CDR as the instrument of monetary policy, the conclusions are once again opposite in nature between China and Russia.

7.3 Few Ideas for Further Research

Since the introduction of the ARCH-M model it has become the most important model in studying the risk-return relationship in the time-varying risk premium framework. As discussed in this thesis, we have focused on the risk-return relationship in two different market conditions in both univariate and multivariate set-up. In the multivariate set-up, apart from the risk-return relationship, the models capture different mean, volatility and volatility-in-mean spillovers in two different - up and down - market situations. In the particular context of this thesis we have worked on the aspect of asymmetric behaviour in two different market situations. But, we think that there are scopes for further work in the following directions.

(i) We have used observed regime switching approach to capture the behaviour and relationships between two stock markets. Here the two market conditions *viz.*, up and down, have been identified by the 'moving average' approach. Though, it is natural that investment and portfolio selection made by the financial agents depend on the past behaviours of the market, it is quite restrictive to make the assumption that market conditions and turning points are observed. It should be possible to estimate these models by taking unobserved regime switching instead of the assumption of observed regime. The unobserved regime switching model, especially, the Markov regime switching model, due to Hamilton (1990), has become very popular in recent years to identify the different market conditions, like bull-bear or up-down, and hence it would be exciting to try to estimate the risk-return relationship under different market conditions using this unobserved regime switching model.

(*ii*) Another direction for further work could be in the area of dynamic conditional correlation model used for representing the contagion effects of financial variables. In recent years, some generalizations of dynamic conditional correlations have appeared in the literature. In the simple DCC model, the conditional correlation matrix is linear function of the lagged conditional correlations and the white noise process. But, there are some studies which have taken nonlinear dependences of the conditional correlation matrix. On the other hand, a few studies have considered the Markov switching-DCC model where the parameters involved in the DCC model are regime specific (see, Billio and Caporin (2005) for details). This model is quite general in the sense that the dynamics of the conditional correlation of asset returns is different in different market conditions. But this model has not been applied in the multivariate GARCH-in-mean framework to analyse the risk-return relationship.

(*iii*) It is evident in the literature of the DCC model that the conditional correlation is higher in the bear/down market and lower in the bull/up market. So, any shock of a particular stock market is transmitted faster to the other stock market in the bear/down situation than in the bull/up situation. On the other hand, other financial variables like exchange rate, interest rate *etc.* are highly related with stock returns. Hence, it can be checked whether any other financial variables have roles in controlling the conditional correlation of a stock market with the overseas stock markets. By using the time varying transition probability Markov switching model along with the DCC-GARCH model, we can check whether any change in other related variables can change the probability of switching the stock market from one regime to the other as well as determine the conditional correlation between the stock markets.

(*iv*) Finally, the Markov switching VAR model with time-varying transition probability may better explain the relationship between stock returns and monetary policy as monetary policy instruments are not purely exogenous. Hence attempts may be made to look into such a modelling framework.

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