ESSAYS ON FINANCIAL VOLATILITY

by

HAKKI ARDA TOKAT

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Thurston, Thom B., Professor

Date

Chair of Examining Committee

Thurston, Thom B., Professor

Date

Executive Officer

Thurston, Thom B., Professor

Wu, Liuren, Associate Professor

Agbeyegbe, Terence D., Professor

Supervision Committee

THE CITY UNIVERSITY OF NEW YORK

ABSTRACT

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Hakkı Arda Tokat

Advisor: Professor Thom B. Thurston

Explaining the variation in asset prices is a fundamental problem of financial economics. As the financial volatility represents uncertainty and is taken as the risk component in financial analyses, its explanation is crucial for financial decision making. In this context, modeling the dynamics of volatility observed in financial asset returns has become the fundamental issue of finance literature.

The first part of the thesis elaborates the issue of high volatility persistence in stock returns. From the previous literature, it is well known that ignoring regime changes in standard GARCH models results in overestimation of volatility persistence. In this study, volatility pattern in Istanbul Stock Exchange is re-examined by considering the potential regime changes in volatility. By applying the iterated cumulative sums of squares (ICSS) algorithm on weekly data of ISE30 and ISE100 indices, regime change points in variance are endogenously detected. This information is integrated to a GARCH(1,1) model and it is found that the volatility persistence is not as high as it has been previously shown in the literature. The results have important implications for financial investors and question the common perception that the volatility in financial markets is highly persistent.

The last part of thesis deals with the issue of volatility spillover and examines the volatility transmission mechanism among the developed and emerging CDS markets by employing multivariate GARCH modeling. As the globalization resulted with more integration of financial markets, it is important for market participants to know how the shocks and volatility are transmitted over time across the markets. Significant transmission of shocks and volatility is found among different CDS markets. Contrary to previous studies showing one-way transmission of volatility from developed to emerging markets, interdependence detected among the different markets indicates the presence of cross-market hedging.

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I want to devote this study to my kids Mert Adil, Kadriye Deniz, my father Adnan Tekin Tokat and to my grandmother Kadriye Akinci with my love and…

Respect …

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1.1. Introduction

Explaining the variation in stock market prices is a fundamental problem of financial economics. As the stock market volatility represents uncertainty and is taken as the risk component in financial analyses, its explanation is crucial for financial decision making. In this context, modeling the dynamics of the variance of stock returns by an ARCH specification has become very popular since its introduction by Engle (1982) and Bollerslev (1986). The variants of the GARCH model have been extensively used in modeling financial time series data.

One common implication of conditional variance models is high estimated persistency of shocks to volatility. Determining the volatility persistence is an important step in financial analyses as it is shown in Poterba and Summers (1986); an increase in expected volatility persistence reduces current asset prices. However, it has also been shown that volatility persistence is overestimated when regime shifts are ignored in modeling conditional volatility (Lastrapes, 1989). Given the key role of volatility persistence in current asset prices and the impact of regime shifts on volatility persistence, the detection of changes in volatility regimes is critical in portfolio and risk management.

This paper first detects the time periods of sudden changes in return volatility and then introduces this information as a new parameter into a volatility model to re-examine the volatility persistence in Turkish stock exchange market. The Turkish stock market is a particularly motivating case to study as it holds a number of distinct characteristics. Firstly, it is the largest and one of the most liquid markets in the MENA region (Middle East and North African). Besides its regional dominance, Turkish stock market has been the magnet for foreign investors in the post-2001 crisis period. The Istanbul Stock Exchange (ISE) market hit its historical high at the beginning of 2006 and foreign capital flows has been shown to be the driving force for the accelerated upward movement[1]. Despite of its increasing popularity, Turkish stock market has also been characterized by its high volatility component. For example, between the period from 1990 to 2005, Turkey, along with Brazil, has a quite high level of volatility (as measured by standard deviation) in weekly local returns, at 0,071 (Brazil with 0,076). As a comparison, during this time period, Chile and South Africa were among the less volatile emerging markets, with standard deviations of 0,024 and 0,026, respectively[2].

In light of the highly volatile behavior of ISE, it is important to examine the presence of any sudden changes in variance. Clearly, any finding on the impact of these sudden shifts on measured or estimated volatility persistence would be quite useful information for financial investors as well as policymakers. An accurate assessment of return volatility is critical for implementing international portfolio diversification and hedging strategies and assumes significance for proper evaluation of monetary policy changes that aim at managing international capital flows.

[1] IMF, Global Financial Stability Report, April 2006
[2] These figures are calculated by using the data from Global Financial Database.

As mentioned earlier, volatility persistence is overestimated when standard GARCH models are applied to series with underlying sudden changes in variance. Then, the standard GARCH model should be augmented with regime shifts to get reliable parameter estimates of the conditional variance equation (Lamoureux and Lastrapes, 1990a).

However, most of the studies use models with a pre-specified number of regime shifts. As an alternative to augmented GARCH modeling, dividing the financial time series into sub-periods by determining the potential break points is another approach used in the previous literature. In an analysis of volatility behavior in Istanbul Stock Exchange, Aygören (2006), investigates whether there are regime shifts in volatility by considering the structural breaks and dividing the data set in to five sub-periods. Sub-periods are determined exogenously and the important economic and political events, crises that occurred in the sample period are chosen as the structural break points. However, specifying the number of structural breaks is not easy under the conditions of emerging stock markets; each with unique characteristics and is subjected to frequent structural economic, political and social changes. A solution to this problem is to determine the regime shifts endogenously. In this study, the shifts in volatility are detected by using iterated cumulative sums of squares (ICSS) algorithm. The ICSS method permits to detect the number of sudden changes in times series, and also to estimate the time point and the magnitude of each sudden change which could be in both negative and positive direction. As the ICSS algorithm assumes constant variance within a regime, which contradicts with the heteroskedastic behavior of financial data, a modified version of the model, taking care of the conditional heteroskedasticity, is used for the analysis.

Weekly returns of ISE100 and ISE30 indices are examined from January 1990 to April 2007. For ISE 30 index, three sudden changes points associated with four different volatility regimes are detected. Owing to longer data span, the examination of ISE 100 index indicates six break points in variance and seven distinct volatility regimes. The standard GARCH model is augmented with a set of control variables to account for sudden changes in variance. The comparison of the results of standard GARCH model and the augmented GARCH model reveals that the volatility persistence is significantly reduced when the regimes shifts are considered in volatility. It is believed that the context of this research is very appropriate, since the volatility in stock markets has been a priority for investors and policymakers during the current worldwide financial crisis.

1.2. Literature Review

One stylized fact about stock-return data is that the returns are leptokurtic. This property leads to volatility clustering and implies that the conditional variance of stock returns may be time dependent. This time-varying property of series suggests that the shocks to the stock prices may affect the volatility for a certain period of time into the future. Volatility persistence which can be described as the dependence of current volatility on past volatility is an important economic issue. As Poterba and Summers (1986) shows the degree of impact of stock-return volatility on stock prices significantly depends on the permanence of shocks to variance. Particularly in the area of financial engineering, pricing of options significantly relies on the underlying asset’s volatility. For instance, a transitory shock will have a smaller impact on the price of an option with a certain time to maturity than a shock which is mostly permanent. Thus, effective modeling of volatility persistence is a key point of understanding such issues in finance area.

Early research on time-varying volatility obtained volatility estimates from stock returns data before specifying a parametric time-series model for volatility. Officer (1973), for instance, used rolling windows and measured the standard deviation measured of stock returns over a sub-sample which moves forward overtime to estimate the volatility at each point in time. Other researchers such as Garman and Klass (1980) and Parkinson (1980) measured the difference between the high and low prices on a given day to estimate volatility for that day. One common assumption of these methods is that the volatility is constant over some time interval of time.

In contrast to the assumption of constant volatility over some period of time, later research on volatility estimates specifies a parametric model first and then uses the model to obtain volatility estimates from the returns data. In this context, the ARCH model developed by Engle (1982) and later generalized by Bollerslev (1986) has been one of the most popular methods used for modeling conditional variance. The generalized autoregressive conditional heteroskedasticity (GARCH) model allows the conditional variance to be an autoregressive moving average (ARMA) process i.e. shocks to conditional variance persists according to an ARMA structure of the squared residuals of the process. Parallel to the extensive use of ARCH models, strong evidence on persistence of volatility in financial time-series data has been obtained, which motivated Engle and Bollerslev (1986) to introduce the integrated-GARCH (I-GARCH) process. In I-GARCH specification, shocks to variance do not necessarily decay overtime which is analogous to a unit root in the mean of a stochastic process.

Lamoureux and Lastrapes (1990a) point to the lack of theoretical background on I-GARCH modeling and investigate the possibility that the presence of high persistence in volatility in daily stock return series may be due to time-varying GARCH parameters. Specifically, they claim that the volatility persistence may be overestimated due to the existence of, and failure to take account of, deterministic or structural shifts in the model. By an analysis of daily stock return data and a Monte Carlo simulation experiment, they confirm their hypothesis that the GARCH measures of persistence in volatility is sensitive to model misspecifications such as ignoring the presence of structural shifts in the financial time-series data.

Lamoureux and Lastrapes (1990b) also point out the effect of the size of financial time series data on volatility persistence. As referring to Chou (1988) who shows that the temporal aggregation of the financial time-series data reduces the measured persistence in GARCH models, they estimated GARCH (1,1) models over a sample of 300 observations for daily returns on 20 individual stocks. The volatility persistence for those individual stocks was found to be smaller i.e. 0,728 than might be expected given the previous GARCH literature which studied with much longer time series. As a comparison, French, Schwert and Staumbaugh (1987) obtained a sum of GARCH parameters to be 0.997 with a sample of over 15,000 observations of daily stock returns.

Diebold (1986) suggested a potential explanation for estimation of low GARCH parameters over small samples by pointing at the possible instability or nonstationarity of unconditional variance over the long sample periods. Lastrapes (1989) confirmed this possibility by showing that the exchange-rate volatility which is modeled by ARCH specification depends on U.S. monetary policy regimes. By use of dummy variables controlling the regime changes, Lastrapes (1989) provides evidence on diminishing degree of ARCH persistence and concludes that the longer the sample period, the higher the probability of regime changes. Thus if the regime changes are controlled for, sample size becomes smaller in which the unconditional variance is possibly stationary.

The literature on changes of variance starts with Hsu, Miller and Wichern (1974), who proposed a normal probability model with a nonstationary variance subject to step changes at irregular time points. Identifying the point of change in a sequence of independent random variables has been the subject of many research studies (Hinkley 1971, Menzefricke 1981, Smith 1971, 1980). Hsu (1977,1979, 1982) studied the detection of a variance shift at an unknown point in a sequence of independent observations but focused on detection of one point of change at a time due to the computational difficulties in searching for multiple change points simultaneously. Baufays and Rasson's (1985) method, on the other hand, handles several change points simultaneously and reduces the computational complexity by estimating the variances and the change points of maximum likelihood.

The issue of estimation of the number and location of structural change has also been a popular field of research in areas other than finance (Andrews, Lee, and Ploberger, 1996; Garcia and Perron, 1996; Bai, 1997; Bai and Perron 1998; 2003a,b). The techniques developed in these studies are mostly for estimation and location of multiple change points in the mean parameters of trend models. However, as Bai and Perron (1998) assert, they can also accommodate changes in the variance.

Bai and Perron's (1998) procedure can be described as follows. When the break point is found at period k, the whole sample (T observations) is divided into two subsamples with the first sub-sample consisting of k observations and the second containing the remaining (T-k) observations. A break point is then estimated for the sub-sample where a hypothesis test of parameter consistency is rejected. The corresponding sub-sample is then divided into further subsamples at the estimated break point and a parameter constancy test performed for the hierarchical subsamples. The procedure is repeated until the parameter constancy test is not rejected for all subsamples. The number of break points is equal to the number of subsamples minus 1.

One widely accepted and used approach to testing for volatility shifts is Inclan and Tiao (1994)'s Iterative Cumulative Sums of Squares (ICSS) algorithm. Their approach uses cumulative sums of squares to search for change points systematically at different pieces of the series. It is based on a centered version of the cumulative sum of squares presented by Brown, Durbin and Evans (1975). They develop an algorithm to find multiple change points in an iterative way. This algorithm allows for detecting multiple breakpoints in variance in a time series. Aggarwal, Inclan and Leal (1999) present an application of this procedure for emerging markets over 1985-1995. They conclude that most events leading to volatility shifts tended to be local (e.g., the Mexican peso crisis, periods of hyperinflation in Latin America), and that the only global event over the sample that affected several emerging markets was the October 1987 crash.

1.3. The Turkish Stock Exchange

Istanbul Stock Exchange was launched in December 1985 and trading started on January 3rd, 1986. The number of listed companies as of 31 December 1986 was 80 and this number increased to 316 as of 31 December 2006. Market capitalization was 938 million USD as of 31 December 1986 whereas it reached 163,775 million USD as of 31

December 2006. As it can be seen from this trend, the Istanbul Stock Exchange has been one of the fastest growing emerging markets in recent two decades. There are two basic price indices, ISE30 and ISE 100, which are calculated and published by Istanbul Stock Exchange. From those indices, ISE-100, which has been calculated since the inception of the ISE, is composed of National Market companies except investment trusts. The constituents of the ISE National-100 Index are selected on the basis of pre-determined criteria directed for the companies to be included in the indices. ISE-30 is composed of National Market companies except investment trusts and is also used for trading in the Derivatives Market. The constituent 30 companies are selected on the basis of pre-determined criteria directed for the companies to be included in the indices. Although there are other price indices, these two indices are the most referred ones, ISE-100 as being the main market indicator and ISE-30 as the most heavily traded futures' underlying asset in Turkish Derivatives Exchange.

1.4. Methodology and Data

The statistical analysis used in this study to test for the persistency of volatility shocks under the presence of regime shifts is conducted as a two-step procedure. In the first step, sudden change points in the variance of stock returns are detected based on ICSS algorithm introduced by Inclan and Tiao (1994). The detected break points indicate the time at which discrete shifts in the variance of stock returns occur. The analysis of events corresponding to the periods of volatility changes is followed by the second step which is calculating the volatility persistence in the presence of those breaks.

1.4.1. Detection of Sudden Changes in Variance

Inclan and Tiao's (1994) ICSS (*the iterated cumulative sums of squares*), algorithm focuses on detecting the occurrence of changes in variance in time series due to a sudden shock that changes the variance until a next shock. The method assumes stationary variance of a time series over an initial period of time until disturbed by an exogenous shock, thus resulting in a sudden change in variance. Let ε_t be a series with zero mean and unconditional variance σ^2_t. Let the variance within each interval is given by τ^2_j, j=0, 1… N_T, where N_T is the total number of variance changes over T observations, and $1 < \kappa_1 < \kappa_2 < \ldots < \kappa_{NT} < T$ are the corresponding change points,

$$\begin{aligned} \sigma^2_t &= \tau^2_0 \quad 1 < t < \kappa_1 \qquad (1) \\ &= \tau^2_1 \quad \kappa_1 < t < \kappa_2 \\ &\ldots \\ &= \tau^2_{NT} \quad \kappa_{NT} < t < N_T \end{aligned}$$

Denote C_k, as the cumulative sum of squared observations from the first observation to the kth point in time. Define D_k statistic as:

$$D_k = (C_k/ C_T) - k/T \qquad k=1,\ldots, T \text{ with } D_0= D_T=0 \qquad (2)$$

If the series has constant variance, D_k will look like a horizontal line when plotted against k. However, if there is a sudden change in variance, the D_k value will plot as a positive or negative drift away from zero. Significant changes in variance are determined by the critical values obtained from the distribution of D_k under the null hypothesis of no change in variance. If the maximum absolute value of D_k is greater than the critical value, then the null hypothesis of homogenous variance is rejected. Let k* is the value at which $\max_k \sqrt{T/2}|D_k|$ is obtained. If the maximum of $\sqrt{T/2}|D_k|$ is larger than the predetermined boundary, then k* is taken as the time point of a structural break. The factor $\sqrt{T/2}$ standardizes the distribution.

Aggarwal, Inclan and Tiao (1999) use a critical value of 1.36 which is the 95th percentile of the asymptotic distribution of $\max_k \sqrt{T/2}|D_k|$ and set the upper and lower boundaries at ±1.36 in the D_k plot. However, the assumption of constant variance within each regime has to be taken care of as the financial data is known to show conditional heteroskedasticity. We follow Malik (2005) and Sanso, Arago, and Carrion (2004) and use the critical value of 1.4058 which corrects for kurtosis and explicitly accounts for conditional heteroskedasticity. Sanso *et. al.* (2004) obtained this higher critical value from a series of fitted response surfaces on powers (p_j=0) of the sample size for a 5% significance level via Monte Carlo simulations. In case of failure to properly adjust the critical values, the null hypothesis will be over-rejected and thus the standard ICSS algorithm is likely to detect more spurious breakpoints on conditionally heteroscedastic data. Sanso *et. al.* (2004) confirm this claim by using Monte Carlo simulations and present examples from real financial data.

Additionally, when the entire series is examined simultaneously, multiple change points are difficult to detect due to the “masking effect”. Therefore, Inclan and Tiao (1994) designed an iterative algorithm based on repeated applications of D_k on different segments of the series, dividing consecutively after a change point is identified. After the change points have been detected, the next step analyzes the corresponding events during the periods of change in volatility.

1. 4.2. The GARCH Model

A common way to measure volatility of economic and financial time series is the simple (unconditional) standard deviation. However, these standard deviations ignore pertinent information on the random process generating variable and they also distort the nature of volatility pattern due to smoothing (Bini-Smaghi, 1991). A basic observation particularly about asset return data is that large returns (of either sign) tend to be followed by more large returns (of either sign). In other words, the volatility of asset returns appears to be serially correlated. To capture this serial correlation of volatility, Engle (1982) introduces the class of Autoregressive Conditionally Heteroskedastic, named ARCH models. In an ARCH framework, conditional variance is modeled as a distributed lag of past squared innovations:

$$h_t = \omega + \alpha(L)\varepsilon^2_t \tag{3}$$

where $\alpha(L)$ is a polynomial in the lag operator.

Bollerslev (1986) extended Engle's original work by developing a technique that allows conditional variance to be an ARMA process. As a way to model persistent movements in volatility without estimating a large number coefficients in a high-order polynomial $\alpha(L)$, Bollerslev (1986) suggested the Generalized Autoregressive Conditionally Heteroskedastic, named GARCH, model:

$$h_t = \omega + \alpha(L)\varepsilon^2_t + \beta(L)h_t \tag{4}$$

where $\beta(L)$ is also a polynomial in the lag operator. Similar to ARMA models, the model is called GARCH(p,q) model when the order of polynomial $\beta(L)$ is p and the order of polynomial $\alpha(L)$ is q.

1.4.3. ICSS-GARCH Combined Model

Since the interest here is to investigate the sudden changes in volatility, I focus on the estimation of a simple but most commonly used standard GARCH model, GARCH (1,1). The GARCH (1,1) model can be written as

$$R_t = \mu + R_{t-1} + \varepsilon_t, \qquad \varepsilon_t | I_{t-1} \sim N(0,h_t) \tag{5}$$

$$h_t = \omega + \alpha\varepsilon^2_{t-1} + \beta h_{t-1} \tag{6}$$

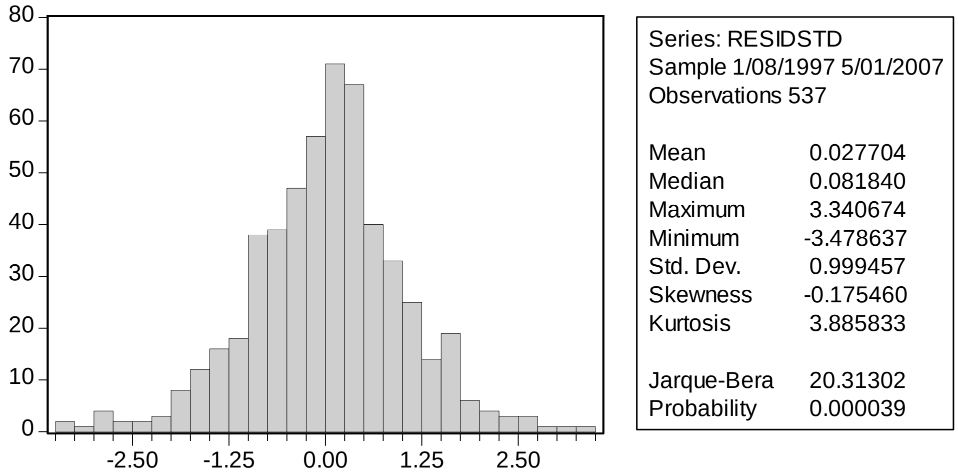
where R_t is the return series, N is the conditional normal density with a zero mean and variance h_t and I_{t-1} is the information set available at time t-1.

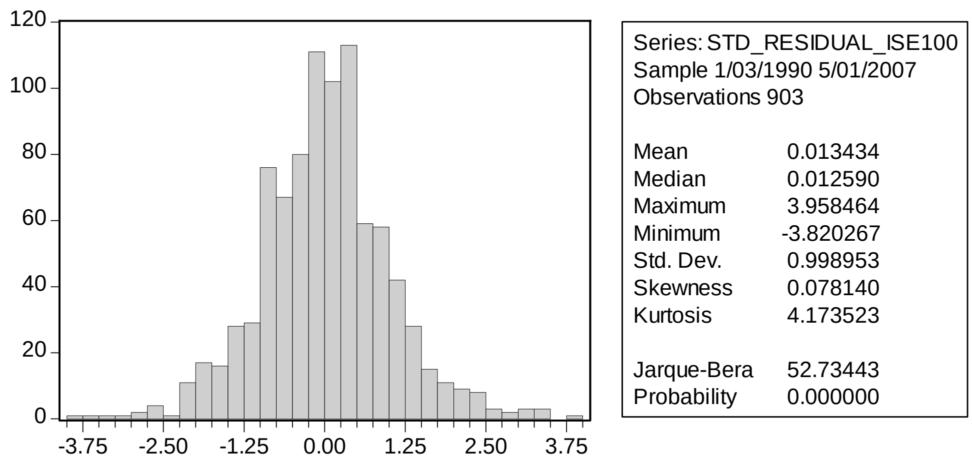
One of the basic assumptions of standard GARCH models is that the standardized error terms are normally distributed. However, in practice there is excess kurtosis in the standardized residuals of GARCH models as it showed itself in my estimations as well (see Chart 1). Kurtosis measures the peakedness or flatness of the distribution of the series. Kurtosis is computed as

$$K = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{y_i - \bar{y}}{\hat{\sigma}}\right)^4 \tag{7}$$

where $\hat{\sigma}$ is based on the biased estimator for the variance ($\hat{\sigma} = s\sqrt{(N-1)/N}$). The kurtosis of the normal distribution is 3. If the kurtosis exceeds 3, the distribution is peaked (leptokurtic) relative to the normal. In my GARCH (1,1) estimations, standardized residuals-ε_t show leptokurtic behavior with kurtosis higher than 3 (Figure 1). As a way of handling this problem, robust standard errors were calculated by using the method of Quasi-maximum likelihood estimation which yields unbiased standard errors even if the distribution is not normal (Bollerslev and Wooldridge, 1992).

Chart 1. Standardized Residual Series Obtained from GARCH(1,1) Model For ISE30 and ISE00 Return Series.





The ICSS algorithm is applied to the residual series (ε_t) obtained from the equation *(5)*. Following the detection of sudden change points in variance by ICSS algorithm, dummy variables are introduced into the variance equation of the GARCH model to account for the shifts in the volatility in stock returns. Then the ICSS-GARCH combined model is given by

$$R_t = \mu + R_{t-1} + \varepsilon_t \qquad \varepsilon_t | I_{t-1} \sim N(0, h_t) \qquad (8)$$

$$h_t = w + \sum_{i=1}^{n} diDi + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1} \qquad (9)$$

where following Aggarwal, Inclan and Leal (1999), D_i is a step function dummy variable taking the value of one from the point of a sudden change in variance onwards and a value of zero otherwise, and n is the number of volatility regimes as identified by the ICSS procedure. Additionally, an autoregressive process of order one, AR(1), specification for mean equation is used if a series shows significant autocorrelation as detected by the Ljung-Box Q-statistic.

1.4.4. Data

The data consist of daily closing values for the Istanbul Stock Exchange (ISE) 100 and ISE 30 indices. Data cover the 16-year period January 1990-April 2007[3]. For the analysis, the daily stock market indices are transformed into weekly rates of return based on Wednesday prices. If there was no trading on Wednesday, the stock index value of the last trading day is used. The analysis used weekly rather than daily returns as it is expected to cause fewer problems than daily data do because of non-synchronous trading and short-term correlations due to noise. Consistent with the literature, the return series are generated as:

$$R_t = \log(P_t) - \log(P_{t-1}))$$

where P_t is the price index.

1.4.5. Descriptive Statistics

Table 1 presents descriptive statistics for ISE 30 and ISE 100 weekly return series. Both series are found to be leptokurtic (fat tails) with extra kurtosis. The mean and the standard deviation are the same for both series. The volatility pattern can be observed from the plot of daily returns of each series in Chart 2. Since no significant

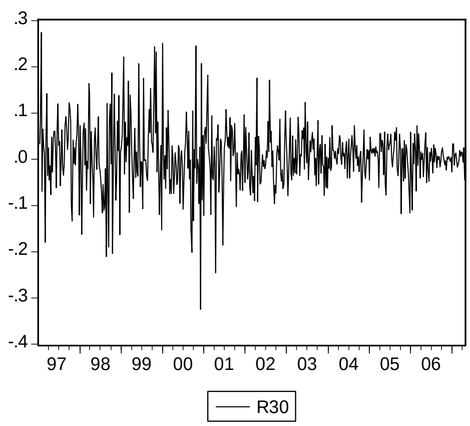
[3] Series for ISE30 starts from 01.01.1997.

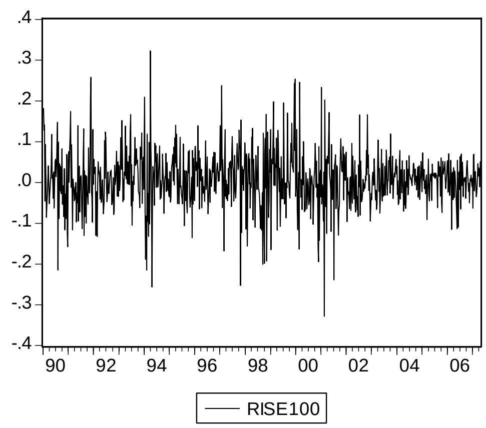
autocorrelation is detected by Ljung-Box statistics in neither series, the mean equations are modeled without an AR(1) specification.

Table 1. Descriptive Statistics for Istanbul Stock Exchange ISE100 and ISE30 Index Returns

Series	Mean	Std. Deviation	Kurtosis	Q(16)	N
ISE30	0.0071	0.069	5.75	18.66	537
ISE100	0.0084	0.069	5.53	14.86	903

Chart 2. Daily Returns of ISE30 and ISE100 indexes





1.5. Empirical Results

Table 2 reports the number and time of sudden changes in variance detected by the ICSS algorithm. For ISE 30 index, there are two break points and so three different volatility regimes are detected. One interesting point is the decreasing trend in volatility except the last period. The break points which are perceived as an improvement and resulted with decrease in volatility seem to be affected generally by the government's announcements on privatization efforts, introducing of policies empowering the banking system in the aftermath of 2001 financial crisis (July 11th, 2001) and the new laws passed as a result of policies followed for EU membership (October 8th, 2003).

For ISE100 index, six break points and seven different volatility regimes are detected, which can be attributed to a larger data set. Again, as a result of reforms and financial liberalizations policies (passing of insiders' trading law, etc.) at the beginning of nineties, decreasing trend in volatility is observed (February 26, 1992). While the effects of the 1994 crisis is seen in the short lasting third volatility period (SD=0.143), the government's announcement on the new welfare policy for decreasing the budget deficit and fighting with inflation (April 24th announcements), coincides with the break point where the lower volatility period has started (April 27th, 1994).

Surprisingly, the only global event that affects the Turkish stock market seems to be the 1997 Asian crisis; the break point at which the volatility is climbed to a higher level happens to be at the same time with Asian crisis. Chart 3 graphically shows the break points of conditional variance and related volatility regimes for ISE30 and ISE100 indexes. Within the bands of ±3 standard deviation, the start and the end of volatility regimes can be seen clearly.

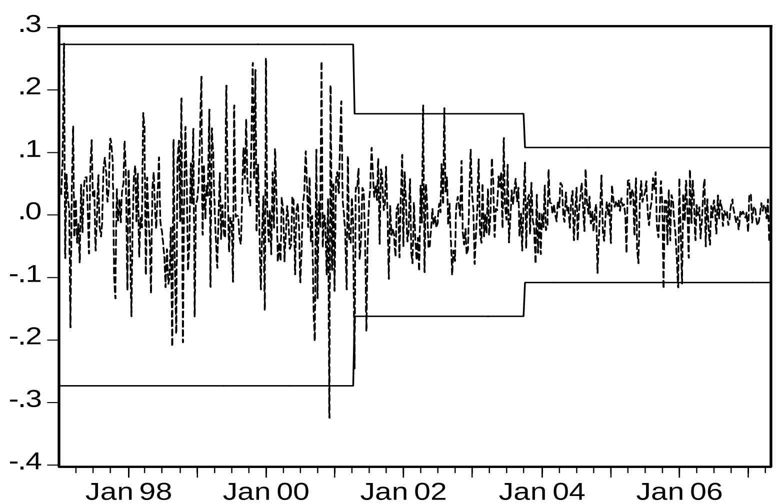
In sum, it can be stated that the economic and political events referred above and the break points and regime shifts in volatility detected by ICSS algorithm are related to some extent. On the other hand, it should also be considered that the market participants form their expectations in advance and react accordingly. Thus, instead of connecting the detected break points with these events, it makes more sense to conclude that; important political changes and financial crises may be a contributing factor in the sudden change of conditional variance. The purpose in this paper is to identify the time periods of sudden changes in volatility rather than inspection the factors causing the sudden changes.

Table 2. Structural Break Points in Volatility

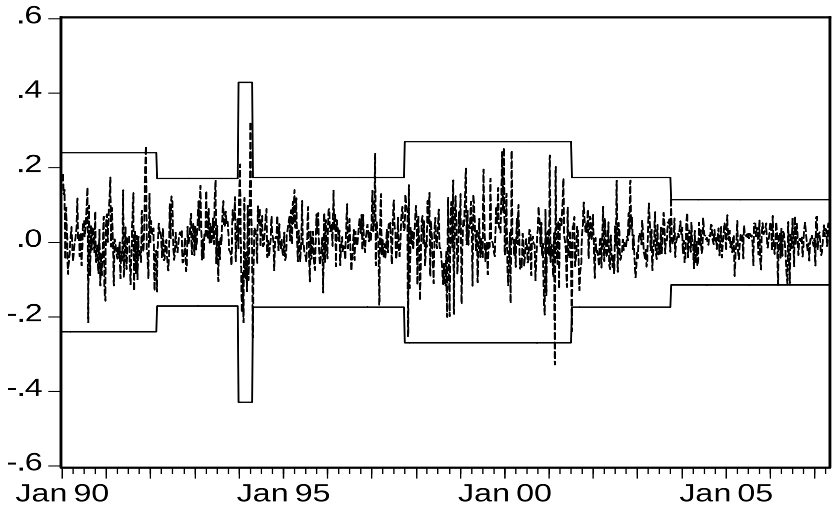
	# of Break Points	Period	Standard Deviation
ISE30	2	1 January 1997 – 10 July 2001	0.091
		11 July 2001- 7 October 2003	0.054
		8 October 2003- 25 April 2007	0.036
ISE100	6	3 January 1990 – 25 February 1992	0.080
		26 February 1992 – 28 December 1993	0.057
		29 December 1993 – 26 April 1994*	0.143
		27 April 1994 – 30 September 1997	0.058
		1 October 1997 – 10 July 2001*	0.090
		11 July 2001 – 7 October 2003	0.058
		8 October 2003 – 25 April 2007	0.038

* period of increasing volatility

Chart 3. Return of ISE30 and ISE100 indexes
3.a. ISE 30



3.b. ISE 100



The next step after detecting the break points is including these points in the standard GARCH model. First, following Aggarwal, Inclan ve Leal (1999), dummy variables representing the detected break points and controlling the different volatility regimes are added into the variance equation of GARCH(1,1) model. As Lamoureux ve Lastrapes (1990b) stated, when regime shifts are taken into consideration, the persistence of estimated volatility shocks are significantly diminishing. To elevate this point, GARCH model without controlling the regime shifts is also estimated and the results are reported in Table 3.

Table 3. GARCH (1,1) Models

	α	Β	α + β	Wald Test χ^2	TR^2	Q(16)
			Standard GARCH Model			
ISE 30	0.08	0.915	0.995	0.52	0.061	0.616
	(0.000)	(0.000)		(0.47)	(0.98)	
	[0.019]	[0.018]				
ISE 100	0.129	0.847	0.976	1.97	0.382	0.206
	(0.000)	(0.000)		(0.163)	(0.764)	
	[0.0018]	[0.031]				
			ICSS – GARCH Combined Model			
	α	Β	α + β	Wald Test χ^2	TR^2	Q(16)
ISE 30	0.025	0.85	0.875	3.38	0.046	0.735
	(0.25)	(0.000)		(0.07)	(0.986)	
	[0.022]	[0.07]				
ISE 100	0.047	0.56	0.67	16.18	0.139	0.366
	(0.07)	(0.000)		(0.000)	(0.96)	
	[0.027]	[0.099]				

Notes: The values in the parentheses show p-values, in brackets show standard errors. Q (16) is the Ljung-Box statistic and TR^2 is an ARCH-LM test. Wald Test tests the hypothesis that $\alpha + \beta = 1$.

For the two different indexes, standardized residuals of the two different GARCH models (controlled and uncontrolled regimes) are investigated by ARCH-LM and Ljung-Box test and the results show that there is no problem with the model performance. The interesting point here is that the success of the standard GARCH model might lead the researcher to ignore the regime changes in variances. If the regime changes matter in effecting volatility persistence, then overlooking the sudden changes will be a problem. When estimated results in Table 3 are examined, it is clear that the regime changes do affect the volatility persistence. When the regime changes are considered, the persistence of shocks (the sum of estimated ARCH and GARCH parameters, α+β) is significantly diminishing for both ISE 30 and ISE 100.

As the results suggest, ignoring regime changes in the presence of sudden changes can lead to biased and invalid results on the degree of volatility persistence that exits in stock returns. Therefore, it is vital to test the break points in volatility and if there are any, to control them.

1.6. Conclusion

In this study, the dates of sudden changes in volatility in the Istanbul Stock Exchange over the January 1990- April 2007 period are detected and this information is utilized for GARCH modeling of volatility. Unlike the most previous research on GARCH modeling, the regime shifts are not introduced to the model exogenously but are determined from the data by using ICSS algorithm. Endogenously determined regime shifts are incorporated to the GARCH model and the effect of shocks on volatility persistence is re-examined. As parallel to previous studies (Aggarwal, Inclan ve Leal, 1999; Lamoureux ve Lastrapes, 1990a), it is found that the volatility persistence is significantly reduced when the regime shifts are considered in modeling volatility.

The markets are open to economic and political events and these events may cause sudden changes and regime shifts in financial time series. From this perspective, it is important to interpret cautiously the previous studies showing the high volatility persistence of stock returns. As it is shown in this study, controlling for possible regime changes in conditional variance and use of this information in modeling volatility improves the accuracy of estimation. This approach is believed to be very useful for financial professionals as well as researchers for their portfolio allocations.

CHAPTER II

UNDERSTANDING THE VOLATILITY TRANSMISSION MECHANISM AMONG THE CDS MARKETS

2.1. Introduction

Along with the recent financial turmoil, the issue of volatility interaction has gone on the stage once more, a decade after the Asian crisis. In the last two decades, increasing integration of financial markets throughout the world has already generated interest in knowing how the financial shocks are transmitted across the markets. However, much attention has been focused on examining the volatility interaction mechanism that exists on major financial equity markets. Some important papers studying the volatility interaction and its spillover effects on regional markets are those by Hamao, Masulis, and Ng (1990), King and Wadhwani (1990), Lin, Engle, and Ito (1994), Engle and Susmel (1993), and Karolyi (1995), Tanizaki and Hamori (2008). Volatility transmission literature has also extended its boundaries by studies examining this mechanism on additional markets such as energy markets by Ewing, Malik and Ozfidan (2002), commodity futures markets by Xu and Fung (2005), foreign exchange markets by Kearny and Patton (2000) or sector indexes by Hassan and Malik (2007) but not on credit derivatives markets.

In the wake of recent global credit crisis, the upsurge of interest in studying the interaction between the financial markets is inevitable, particularly in credit derivatives markets where the crisis boomed from. This paper examines the volatility interaction between the CDS markets of developed and emerging markets. During the first stages of crisis in credit markets, emerging markets had been seen as the safe havens of global financial world as they have relatively cleaner balance sheets carrying lower volume of structural financial products which are blamed for the cause of this crunch. However, increasing sovereign CDS spreads for those markets may be a sign that the financial investors put them in the same basket with the developed ones in terms of risk level, (see Chart 4).

In the past decade, the credit derivatives market has experienced rapid growth, and among credit derivatives, the credit default swap (CDS) has become the most widely traded instrument for transferring credit risk. According to survey data coordinated by the International Swaps and Derivatives Association (ISDA), by the end of 2007, the total notional amount of outstanding CDS contracts grew to $62.2 trillion. CDS contracts can help isolate credit risk from other factors affecting bond prices such as illiquidity premiums, and thus may provide more accurate pricing and cleaner measurement of credit risk than is available from the underlying debt markets.

Chart 4. Credit Default Swap Index of Sovereign Issuers from Three Regions: Latin America, Eastern Europe, the Middle East and Africa, and Asia.

Considering the CDS market's rapid growth, a limited number of work has been done on CDSs that focus mostly on pricing determinants, performance of pricing models, and the majority has concentrated on corporate CDSs such as Blanco et al. (2005). They investigate the long- and short-term relationships of corporate bonds with their corresponding CDSs and conclude that short-term deviations from theoretical parity are due to a lead for CDS prices over credit spreads in price discovery. Regarding sovereign issuers, Chan-Lau and Kim (2004) examine the equilibrium price relationships and price discovery in the CDS, bond and equity markets for eight emerging countries and find that the CDS and bond spreads converge even in the presence of external market pressures. In a recent study, Diaz Weigel and Gemmill (2006) investigate the creditworthiness of Argentina, Brazil, Mexico, and Venezuela, and find that the monthly variation in measures of creditworthiness for these four countries is driven mainly by global and regional factors rather than country-specific fundamentals. Their results highlight the existence of systematic factors that drive fluctuations in the sovereign spreads of emerging markets.

Early research on volatility interaction has shown the dominance of U.S. based financial markets over the emerging ones (see Arshanapalli & Doukas, 1993; King & Wadhwani, 1990; Lee & Kim, 1993). Moreover, the recent studies point out the growing dependency of emerging markets on the developed financial markets (see Frankel and Roubini, 2001; Dailami and Padou, 2005; Chukwuogor, 2007). In this perspective, the interaction mechanism among the developed and emerging financial markets seems to be overlooked by only focusing on unidirectional dependency from developed to emerging markets.

This time, in contrast to previous research questions on volatility interaction literature, the question raised is whether the volatility is transmitted among the developed and emerging financial markets in both directions with a specific focus on CDS markets. The emerging markets used in the analysis are Brazil and Turkey. I picked these countries based on certain criteria. First, Brazil and Turkey are the two emerging markets which have been evaluated together in the same investment basket by the financial investors. Analysis of these two countries in this paper's context would provide further insight into the portfolio allocation decisions of financial participants. Second, recent changes in Brazilian economy and the upgrading of Brazil to investment grade (triple B minus) by Standard and Poor raises the question whether the market participants are going to separate the baskets for Turkey and Brazil and whether the Brazilian market will have a leading role among the emerging markets. To represent the developed markets, there are corporate CDS indices available for the analysis, namely iTraxx Crossover in

Europe and CDX in North America. The iTraxx Crossover (iTraxx XO) index measures the cost of protecting 50 risky European companies' debt (corporate default risk). In other words, this index refers to CDS of high-yield bonds. The index composition is updated twice a year, with the roll dates of each new index being either March 20 or September 20. Each reference entity is equally weighted. In case of a firm's default, the defaulted firm is removed from the index portfolio and the nominal value of the contract declines by 1/50, i.e. 2 %. The index has been widely used by financial institutions as a hedging tool for a huge variety of risky assets. The CDX index represents the average CDS premium of the 125 most liquid investment-grade companies, located in North America, distributed among the five sub-sectors.

The results of this study indicate that first; there is a volatility interaction mechanism running among the developed and emerging CDS markets. Second, contrary to previous studies showing one-way dependency from developed to emerging markets; Brazilian CDS market is found to affect other markets' volatility through its own shocks as well as its past volatility. The results are revealing for building accurate cross-hedging strategies for financial market participants.

The paper is organized as follows: Section 2 describes the methodology and data. In section 3 we provide the empirical results. I conclude and discuss some of the hedging implications in the last section.

2.2. Background

This section provides a brief overview of the credit derivatives market and, in particular, of credit default swaps. Most credit derivatives market activity relates to mature market issuers, and emerging market issuers comprise only a small share of total market activity. In the past few years, however, emerging market credit derivatives have evolved rapidly, and CDS has become a dominant product in the emerging market structured credit market.

2.2.1 Overview: Credit Derivatives

Although the credit derivatives market is relatively small compared with other derivatives markets, credit derivatives have been the fastest growing financial instruments traded in derivatives markets. In 2000 the total notional principal for outstanding credit derivatives contracts was about $800 billion. By June 2007 this number has grown to over $42 trillion. Credit derivatives are financial contracts that allow credit risk to be transferred from one party to another against credit-related losses. As products, credit derivatives combine two key developments in the financial markets: derivatives and securitization. Most of all, these products are designed to isolate credit risk from other sources of risk such as market risk. Therefore, they allow credit risk to be transferred at a relatively low cost.

The main players in this market are banks, securities houses, hedge funds, and insurance companies. Banks are the biggest buyers and sellers of protection. Insurance companies come second to banks as sellers of protection, followed by securities houses and hedge funds. Due to the complexities involved in dealing with event monitoring, counterparty exposure and pricing, relatively a limited number of participants using sophisticated trading and hedging strategies involved in this market.

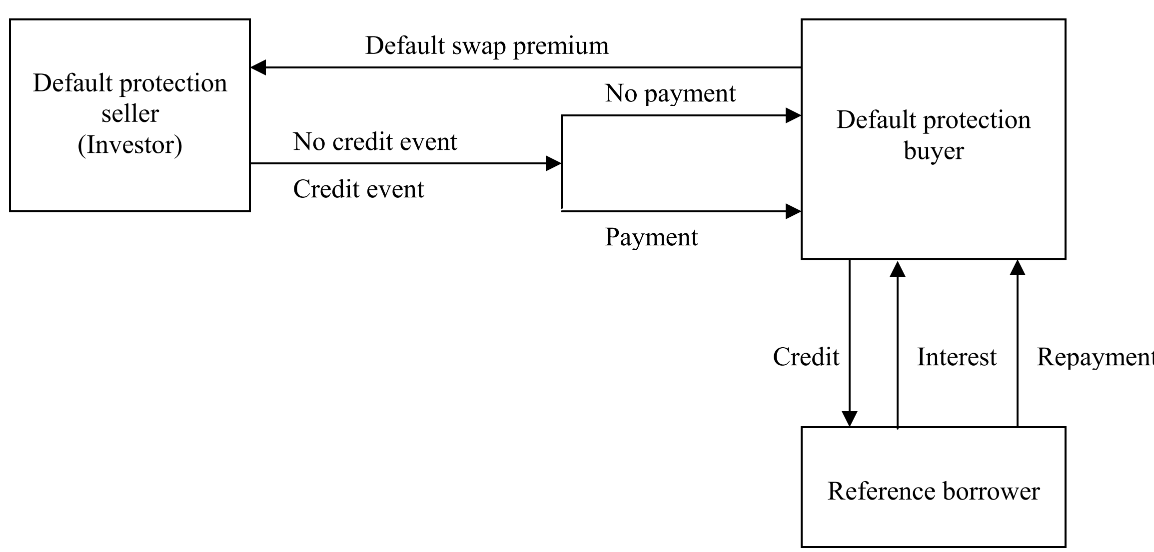
Credit derivatives are usually categorized as “single name” and “multiname”. The most popular single name credit derivative is a *credit default swap* (CDS). The payoff from this instrument depends on what happens to one company or country. A CDS is a swap in which one party makes payments only if a specified credit event (or events) occurs. A *total return swap* is another type of credit derivative which is based on an agreement to exchange the total return on a bond or other reference asset for LIBOR plus a spread. An *asset-backed security* (ABS) is a security created from a portfolio of loans, bonds, credit card receivables, mortgages, auto loans or other financial assets. A type of ABS that has been particularly popular is a *collateralized debt obligation* (CDO). In this instrument, a portfolio of bonds issued by corporations or countries is specified and a complex structure is created where cash flows from the portfolio are channeled to different categories of investors. This is called a *cash CDO*. Recall that a long position in a corporate bond has essentially the same credit risk as a short position in the corresponding credit default swap. This leads to an alternative way of creating a CDO where the collateral is the portfolio of short positions in credit default swaps. This type of CDO is known as *synthetic CDO*. Multiname credit derivatives are increasing in popularity as their share in credit derivatives market increased from 20% in December 2004 to over 43% by June 2007.

2.2.2. Credit Default Swaps

A credit default swap (CDS) is the most liquid product in the credit derivatives market. A CDS is a contract that provides insurance against the risk of a default by particular company. The company is known as the *reference entity* and a default by the company is known as a *credit event.* The buyer of the insurance obtains the right to sell a particular bond issued by the company for its par value when a credit event occurs. The bond is known as the *reference obligation* and the total par value of the bond that can be sold is known as the swap's *notional principal.*

The buyer of the CDS makes periodic payments to the seller until the end of the life of the CDS or until a credit event occurs. In this set up, credit default swaps are analogous to buying insurance against default by the third party referenced in the contract. Typically, the periodic payment or fee is expressed in *basis points* per notional principal of the contract, and the fee is conventionally called a default swap premium or default swap spread. These payments are made in arrears every quarter, every half year, or every year. The settlement in the event of a default involves either physical delivery of the bonds or cash settlement. With physical settlement, the protection buyer delivers the reference obligation (or equivalent) to the protection seller and receives the par amount. With cash settlement, the protection buyer receives a payment equal to the difference between par and the recovery value of the reference obligation, the latter determined from a dealer poll or from price quote services. Most contracts are typically subject to physical settlement. A typical CDS can be settled as in Chart 5.

Chart 5. A Credit Default Swap



2.2.3. Credit Indices

Credit market participants have developed indices to be able to track credit default swap spreads. Two of the most important standard portfolios used for index construction are:

- CDX NA IG, which is a portfolio of 125 investment grade companies in North America
- iTraxx Europe, a portfolio of 125 investment grade companies in Europe.

These portfolios are updated in each year on March 20 and September 20. Companies that are no longer investment grade are dropped from the portfolios and the new investment grade companies are added.

2.2.4. Sovereign CDSs

The development of emerging market credit derivatives (EMCD) corresponds to that of broader derivatives market in the second half of the 1990s. EMCD provide an array of investment and hedging opportunities to the market participants such as hedge funds, emerging market dedicated mutual funds, pension funds, and banks. Hedge funds use these instruments actively either for taking directional bets on the future creditworthiness of a country or to arbitrage the spread differential between the default swap and the referenced bond. Pension funds and emerging market dedicated mutual funds use EMCD products to manage their exposure to emerging market sovereign bonds. Similarly, banks use them to manage their balance sheet exposure to emerging market borrowers.

Credit default swaps are the most basic and most liquid EMCD product and are based on standard International Swap and Derivatives Association (ISDA) contract documentation. Mostly referencing the sovereign issuers, CDS contracts accounts for the 85% of outstanding notional in EMCD. According to Deutsche Bank, the notional amounts outstanding in emerging market credit derivatives in 2002 was US$300 billion, roughly equal to 15 percent of the broader credit derivatives market. CDS contracts are offered in maturities from 1 to 10 years; however, the most liquid segment is in the range of 1 to 5 years.

In general, the liquidity of sovereign CDS depends on the liquidity of sovereign bonds. Not surprisingly, for countries with very large bond markets such as Mexico, Brazil, Russia, and Turkey, it is rather easy to find both CDS bid and ask price quotes. The absence of significant trading in contracts referenced to emerging market corporate issuers reflects both the scarcity of corporate debt issued in foreign currencies and the illiquidity of emerging market corporate bonds.

Hedge funds use CDSs actively either for taking directional bets on the future creditworthiness of a country or to arbitrage the spread differential between the CDS and the referenced bond. Pension funds and emerging market dedicated mutual funds use CDSs to manage their exposure to emerging market sovereign bonds. Similarly, banks use CDSs to manage their balance sheet exposure to emerging market borrowers.

2.3. Methodology and Data

2.3.1. MGARCH Modeling

I used a Multivariate Generalized Autoregressive Conditional Heteroscedasticity (MGARCH) model to identify the volatility interaction relationship between the markets identified in the preceding section. At first, the following the mean equation is estimated for each return series:

$$\Delta \mathrm{p}_{\mathrm{i,t}} = \mu + \alpha \Delta p_{i,t-1} + \varepsilon_{i,t} \qquad (1)$$

where $\Delta p_{i,t}$ is the change in the price of CDS i between time t and $t-1$, μ is a long term drift coefficient, and $\varepsilon_{i,t}$ is the error term for the return on CDS i at time t. The equation is then tested for existing of Autoregressive Conditional Heteroscedasticity (ARCH) using the tests described in Engle (1982). As the volatility interaction between the CDS markets of developed and emerging markets is examined along with the volatility interaction within each market, a variant of multivariate GARCH model is used.

There are number of variations of MGARCH model used in the literature and two of the popular ones are VECH and BEKK models. The VECH model, which was introduced by Bollerslev, Engle, and Wooldridge (1988) is expressed by:

$$\mathrm{vech}(\mathrm{H_t}) = \mathrm{A}_0 + \sum_{j=1}^{q} B_j \, vech(\mathrm{H_{t\text{-}j}}) + \sum_{j=1}^{q} A_j \, vech(\varepsilon_{t-j} \varepsilon'_{t-j}) \qquad (2)$$

where $\varepsilon_t = H_t^{1/2} \eta_t, \eta_t \approx iid\ N(0,1)$. Here, H_t is the conditional variance-covariance matrix, and $vech(\boldsymbol{H_t})$ represents the vector formed by stacking the columns of a matrix, X_t.

There is a more feasible alternative model called BEKK parameterization by Engel and Kroner (1995), which succeeds the complexity associated with VECH parameterization. The BEKK model makes use of quadratic forms so that no restrictions are required to guarantee a positive semi-definite $\mathrm{H_t}$ matrix, a requirement for the estimated variance to be grater than or equal to zero. The BEKK parameterization for multivariate GARCH(1,1) model can be expressed by:

$$H_{t+1} = C'C + A'\varepsilon_t \varepsilon_t^{'} A + B' H_t B \qquad (3)$$

where the elements for eq.3 is expressed as:

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \quad B = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \quad C = \begin{bmatrix} c_{11} & 0 & 0 \\ c_{21} & c_{22} & 0 \\ c_{31} & c_{32} & c_{33} \end{bmatrix} \quad (4)$$

Here, **A** is a 3 x 3 square matrix of parameters that represents the correlation of conditional variances with past squared errors, so the elements of **A** measure the effects of shocks or unanticipated events on conditional variances. **B** is also a 3 x 3 square matrix of parameters that shows how current levels of conditional variances are affected by past conditional variances. **C** is a 3 x 3 lower triangle matrix with six parameters.

For each equation, conditional variance, excluding constants, can be expanded for a trivariate GARCH(1,1) as:

$$\begin{aligned} h_{11,t+1} = {} & a_{11}^2 \varepsilon_{1,t}^2 + 2a_{11}a_{12}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{11}a_{31}\varepsilon_{1,t}\varepsilon_{3,t} + a_{21}^2\varepsilon_{2,t}^2 + 2a_{21}a_{31}\varepsilon_{2,t}\varepsilon_{3,t} \\ & + a_{21}^2\varepsilon_{2,t}^2 + b_{11}^2 h_{11,t} + 2b_{11}b_{12}h_{12,t} + 2b_{11}b_{31}h_{13,t} + b_{21}^2 h_{22,t} + 2b_{21}b_{31}h_{23,t} \\ & + b_{31}^2 h_{33,t} \end{aligned} \quad (5)$$

$$\begin{aligned} h_{22,t+1} = {} & a_{12}^2 \varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{12}a_{32}\varepsilon_{1,t}\varepsilon_{3,t} + a_{22}^2\varepsilon_{2,t}^2 + 2a_{22}a_{32}\varepsilon_{2,t}\varepsilon_{3,t} \\ & + a_{32}^2\varepsilon_{3,t}^2 + b_{12}^2 h_{11,t} + 2b_{12}b_{22}h_{12,t} + 2b_{12}b_{32}h_{13,t} + b_{22}^2 h_{22,t} + 2b_{22}b_{32}h_{23,t} \\ & + b_{32}^2 h_{33,t} \end{aligned} \quad (6)$$

$$\begin{aligned} h_{33,t+1} = {} & a_{13}^2 \varepsilon_{1,t}^2 + 2a_{13}a_{23}\varepsilon_{1,t}\varepsilon_{2,t} + 2a_{13}a_{33}\varepsilon_{1,t}\varepsilon_{3,t} + a_{23}^2\varepsilon_{2,t}^2 + 2a_{23}a_{33}\varepsilon_{2,t}\varepsilon_{3,t} \\ & + a_{33}^2\varepsilon_{3,t}^2 + b_{13}^2 h_{11,t} + 2b_{13}b_{23}h_{12,t} + 2b_{13}b_{33}h_{13,t} + b_{23}^2 h_{22,t} + 2b_{23}b_{33}h_{23,t} \\ & + b_{33}^2 h_{33,t} \end{aligned} \quad (7)$$

The group of equations *(5)*, *(6)* and *(7)* is a representation of how shocks and volatility are transmitted across markets and over time.

In the estimation process, it is assumed that errors are normally distributed and the following likelihood function is maximized:

$$L(\theta) = -T\ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(\ln|H_t| + \varepsilon_t^{'}H_t^{-1}\varepsilon_t) \qquad (8)$$

where θ represents vector of parameters to be estimated and T is the number of observations. Since, the log-likelihood function is non-linear, numerical maximization techniques are used to estimate the model. As recommended by Engel and Kroner (1995), several initial iterations using simplex algorithm are performed to obtain the initial conditions for the BHHH [Berndt, Hall, Hall, and Hausman] algorithm, which in turn provides the final estimate of the variance-covariance matrix with corresponding standard errors.

2.3.2. Data

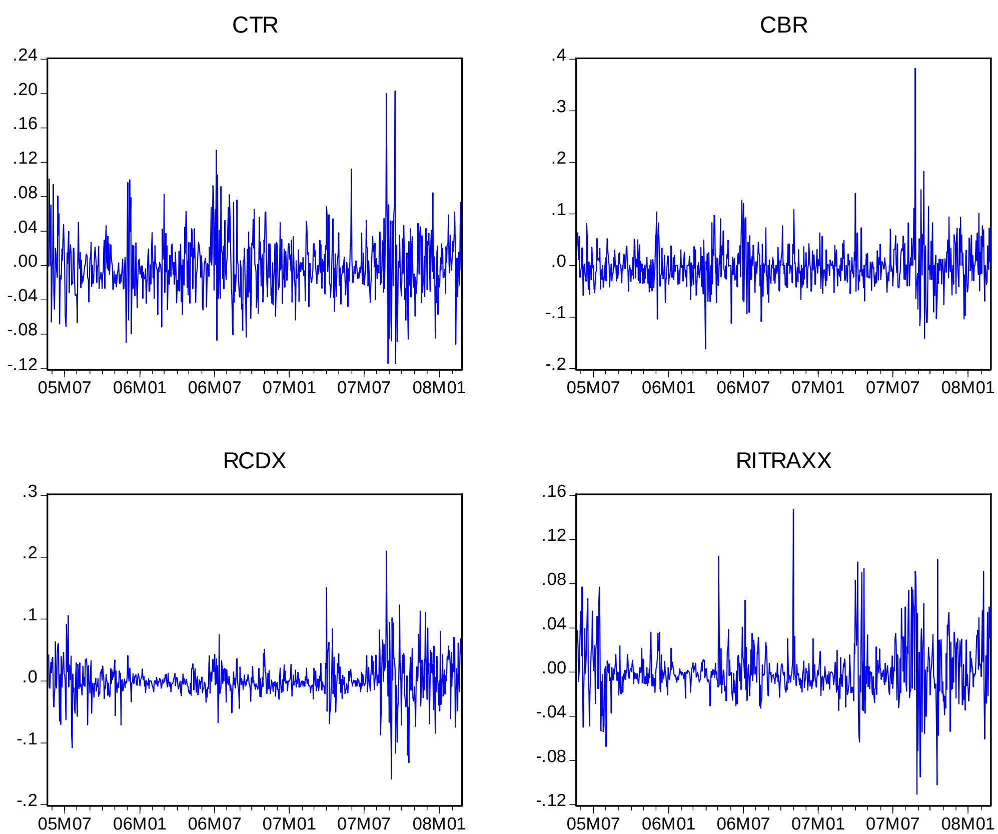
For the analysis of volatility interaction among the CDS markets, I used daily U.S. dollar denominated Turkish and Brazil sovereign CDS prices with a maturity of five years. Sovereign CDS prices and iTraxx XO index of 5-year maturity are obtained from Bloomberg. CDX index of 5-year maturity is obtained from Reuters Ecowin Pro. The sample period spans from May 2005 to February 2008.

The analysis is conducted in the first differences of the log of each variable. Table 4 represents the descriptive statistics of corresponding series. Volatility (as measured by standard deviation) is highest in Brazil CDS market which is followed by Turkish CDS market. The volatility pattern can be observed from the plot of daily returns of each series in Chart 6. As it is fairly common in high frequency financial data, no series are normally distributed. Along with high kurtosis and negative skewness, the Jarque-Bera test provides evidence against the hypothesis of normality is all series (the null hypothesis of Skewness = 0 and Kurtosis = 3). The Q-statistic is used for the detection of autocorrelation and past behavior of the market is found to be significant in all series except Brazil CDS market.

Table 4. Descriptive Statistics for All Return Series

	TR	*BR*	*CDX*	*iTraxx XO*
Mean	-0.000299	-0.001363	0.001383	0.001267
Std. Dev.	0.034540	0.040769	0.030951	0.025076
Skewness	0.730734	1.389215	0.411735	0.869011
Kurtosis	6.765873	15.06873	9.687386	7.721809
Jarque-Bera	488.8508	4594.826	1360.085	758.4313
Probability	0.000000	0.000000	0.000000	0.000000
Q(11)	38.63	15.55	19.82	49.4
Probability	0.0000	0.158	0.048	0.0000

Chart 6. Daily Returns of Turkish CDS, Brazilian CDS, iTraxx XO and CDX



2.4. Empirical Results

Two tri-variate models with four different indicators are the focus of this study. The first model combines (estimates) two emerging markets' sovereign CDS spreads (Turkey and Brazil) with a developed CDS market which is represented by CDX index. In the second model, iTraxx XO index is used as another developed CDS market index.

The estimation results of the multivariate GARCH model with BEKK parameterization for each variance equation are reported in Table 5 and Table 6. The symbol $h_{11,t}$ represents the conditional variance for Turkish CDS market at time *t*, and $h_{12,t}$ represents the conditional variance between the CDS returns of Turkey and Brazil. As explained earlier, the third parameter in two models are different. In the first model, the third parameter represents US market (*CDX*) and in the second model, it represents European market (*iTraxx XO*). The error term ε represents the shocks or news on each parameter, i.e. $\varepsilon_{1,t}^2$ represents the deviation from the mean caused by an unexpected event in Turkish CDS market at time *t*. The cross values i.e. $\varepsilon_{1,t}\varepsilon_{2,t}$ represent the news or shocks in Turkish and Brazilian markets.

While examining the results of both models, only the significant terms at 5% level are discussed. Table 5 reports the estimation results for Turkish and Brazilian CDS market together with CDX index. It's observed that Turkish CDS market is directly affected by shocks in Brazilian market; however, news from U.S. CDS market has an indirect effect on it. Volatility generated from both its own market and Brazilian CDS market seems to affect the Turkish CDS market. The Turkish CDS market is also indirectly affected by both Brazilian and U.S. CDS markets' volatility through the covariance terms.

It’s interesting that Brazilian CDS market is not affected significantly by any shocks or news from any markets examined in the first model. On the other hand, it’s affected by volatility from its own and Turkish CDS markets. It’s also indirectly affected from volatilities generated from both Turkish and U.S. CDS markets. When it comes to CDX index, it’s observed that U.S. CDS market is affected by its own news and indirectly affected by the news from Brazilian CDS market. The volatility from Brazilian market and its own market have an effect on CDX index volatility in the next period. It’s also indirectly affected by the Turkish and Brazilian CDS market volatilities. Based on the first model results, it can be generalized that all markets are indirectly affected by the volatilities from each other.

Table 5. Trivariate GARCH Model for Turkish CDS, Brazilian CDS and CDX index returns

Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{33,t+1}$
$\varepsilon_{1,t}^2$	0.0452*	3.3 $\exp^{-5}$	0.0013
	(1.66)	(0.0449)	(0.7862)
$\varepsilon_{1,t}\varepsilon_{2,t}$	-0.0025	-2.3$\exp^{-4}$	-0.0045
	(-0.0915)	(-0.0731)	(-1.1311)
$\varepsilon_{1,t}\varepsilon_{3,t}$	0.0514**	-0.0029	0.0289
	(2.42)	(-0.0903)	(1.6057)
$\varepsilon_{2,t}^2$	0.1225***	0.00041	0.0041
	(3.31)	(0.1351)	(1.4430)
$\varepsilon_{2,t}\varepsilon_{3,t}$	-0.0846**	0.0101	-0.0519***
	(-2.3152)	(0.2793)	(-2.7355)
$\varepsilon_{3,t}^2$	0.0146	0.0616*	0.1666***
	(1.3160)	(1.8874)	(6.1957)
$h_{11,t}$	0.3706***	0.2102***	0.0034
	(9.7488)	(4.4376)	(1.4141)
$h_{12,t}$	-0.5582***	-0.9910***	-0.0087*
	(-11.291)	(-7.7352)	(-1.9400)
$h_{13,t}$	-0.0961**	-0.0734*	-0.1054***
	(-2.4717)	(-1.7647)	(-2.7947)
$h_{22,t}$	0.1565***	1.1679***	0.0058**
	(5.1699)	(16.75)	(2.2220)
$h_{23,t}$	-0.0624**	0.1730**	0.1374***
	(-2.2132)	(2.0343)	(4.5974)
$h_{33,t}$	0.0062	0.0064	0.8171***
	(1.2720)	(1.0047)	(30.0898)

Note: *, ** and *** represent significance level at 10%, 5% and 1%, respectively.

When it comes to interpret the results for Turkish, Brazilian and European CDS markets, Table 6 should be taken into account. Turkish CDS market is affected directly and indirectly by shocks and news from all markets including its own[4]. The volatility from its own directly and volatility from Brazilian CDS market indirectly affects the Turkish CDS market. Brazilian CDS market is directly affected by shock from its own and from European CDS markets. It's also indirectly affected by shocks from both Turkish and European CDS markets. The volatility from Turkish and Brazilian markets directly affects Brazilian CDS market. There is also indirect effect of Turkish and European CDS markets on Brazilian CDS market. Itraxx XO index seems to be vulnerable to all market shocks and its volatility is directly affected by its own and Brazilian CDS market volatility. There is also robust indirect effect of Brazilian CDS volatility on iTraxx XO index volatility.

In terms of the spillover of shocks from one market to other market's variance, Brazilian and Turkish sovereign CDS markets seem to be more integrated with European iTraxx XO index. This is mostly attributable to model parameters being in the same investment grade. The volatility interaction is more pronounced in the first set up where the U.S. companies' CDS spreads are considered. The iTraxx XO index is generally considered as a leading indicator among the CDS markets by the investors and market professionals. However, the absence of a direct effect of the index volatility on the other two sovereign CDS markets but the significant both direct and indirect transmission of volatility from Brazilian CDS markets to the others calls for a reconsideration of iTraxx XO index as a leading indicator. The leading role of Brazilian CDS market in

[4] In the first model, Turkish CDS market is also affected from its own news occurred in the previous period but the coefficient on $\varepsilon_{1,t}^2$ was significant at only 10% significance level.

transmission of volatility draws attention and it is attributed to its better investment grade along with a stronger economy and sound economic policies.

Table 6. Trivariate GARCH Model for Turkish CDS, Brazilian CDS and iTraxx XO index returns

Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{33,t+1}$
$\varepsilon_{1,t}^2$	0.0462**	0.0320	0.0157**
	(2.1853)	(1.4288)	(2.2578)
$\varepsilon_{1,t}\varepsilon_{2,t}$	-0.0768***	-0.0926**	-0.0387***
	(-3.2531)	(-2.0921)	(-3.0262)
$\varepsilon_{1,t}\varepsilon_{3,t}$	-0.1956***	0.1326***	-0.1966***
	(-3.2640)	(3.0832)	(-3.8531)
$\varepsilon_{2,t}^2$	0.0384**	0.0671***	0.0238***
	(2.2950)	(2.6826)	(3.0371)
$\varepsilon_{2,t}\varepsilon_{3,t}$	0.1782***	-0.1921***	0.2424***
	(3.8708)	(-3.3456)	(5.9810)
$\varepsilon_{3,t}^2$	0.2071***	0.1375**	0.6165***
	(3.3086)	(1.9729)	(5.8551)
$h_{11,t}$	0.9322***	0.0810***	0.0024
	(14.3524)	(3.1815)	(0.7658)
$h_{12,t}$	0.5496***	0.4581***	-0.0090
	(5.6979)	(7.6826)	(-1.2384)
$h_{13,t}$	-0.0710	-0.0587*	-0.0660
	(-1.0030)	(-1.7807)	(-1.4678)
$h_{22,t}$	0.0026	0.6478***	0.0087**
	(0.8644)	(11.8294)	(2.2767)
$h_{23,t}$	0.0037	-0.1660**	0.1264***
	(1.0020)	(-1.9675)	(4.3307)
$h_{33,t}$	0.0014	0.0106	0.4610***
	(0.5067)	(1.0122)	(9.5630)

Note: *, ** and *** represent significance level at 10%, 5% and 1%, respectively.

2.5. Conclusion

A number of studies have investigated the volatility interaction mechanism among the financial markets. In this study, I draw the attention to a relatively new financial instrument, Credit Default Swaps and explore the volatility spillover among the related emerging and developed markets. Multivariate GARCH modeling is employed using daily returns data. The results show that there is a significant interaction among the CDS markets under investigation. Turkish CDS market volatility responds both to unanticipated events and past volatility while Brazilian CDS market volatility depends more on past volatility but not so much on market shocks. The volatility of two CDS indexes, CDX and iTraxx XO, illustrating developed markets do not follow a different interaction mechanism than the emerging markets' volatility, reacting both to market shocks and past volatility. The question raised in this study was whether the volatility is transmitted among the developed and emerging markets in both directions. According to my results, volatility spillover occurs in both directions and there is no sign of the dominance of developed markets in volatility transmission mechanism. Nevertheless, Brazilian CDS market seems to have a leading role; shocks and past volatility of Brazilian CDS market enters significantly into all conditional variance equations. Overall, the interaction of shocks and volatility of the CDS markets is valuable information for financial market participants and may be useful for optimal portfolio decisions. Investors should examine not only the CDS market that they have in their portfolio but also the others since a shock affecting one market will eventually affect the others through the interaction mechanism shown in this study.

BIBLIOGRAPHY

Aggarwal, R., C. Inclan and R. Leal, “Volatility in Emerging Stock Markets”, Journal of Financial and Quantitative Analysis, (1999), 34, 33-55.

Andrews, D. W. K., I. Lee, and W. Ploberger, “Optimal Changepoint Tests for Normal Linear Regression," Journal of Econometrics, (1996), 70, 9-36.

Arshanapalli, B., and J. Doukas, “International Stock Market Linkages: Evidence from the Pre- and Post-October 1987 Period”, Journal of Banking and Finance, (1993), 17, 193-208.

Aygören, H., “An Empirical Analysis of Volatility Behavior for Istanbul Stock Exchange”, Iktisat, Isletme ve Finans, December (2006), 95-110.

Bini-Smaghi, L., “Exchange Rate Variability and Trade: Why is it So Difficult to Find Any Empirical Relationship?”, Applied Economics, (1991), 23, 927-936.

Blanco, R., S. Brennan and I. W. Marsh, “An Empirical Analysis of the Dynamic Relation Between Investment-Grade Bonds and Credit Default Swaps”, Journal of Finance. (2005) 60, 2255–2281.

Bollerslev, T., “Generalized autoregressive conditional heteroscedasticity”, Journal of Econometrics, (1986), 31, 307–27.

Bollerslev, T., R. F. Engle, and J. M. Wooldridge, “A capital asset pricing model with time varying covariance”, Journal of Political Economy, (1988), 96, 116–131.

Cai, A., "Markov model of switching-regime ARCH", Journal of Business and Economic Statistics, (1994), 12, 309–316.

Chan-Lau, J. A., and Y. S. Kim, "Equity Prices, Credit Default Swaps, and Bond Spreads in Emerging Markets", (2004), IMF Working Paper No. WP/04/27

Chou, R. Y., "Persistent Volatility and Stock Returns – Some Empirical Evidence Using ARCH", Journal of Applied Econometrics, (1998), 3, 279-294.

Chukwuogor, C., "Stock Markets Returns and Volatilities: A Global Comparison", Global Journal of Finance and Banking Issues, (2007), 1 (1), 1-27.

Dailami, M., and M. Padou, "Global Monetary Conditions Versus Country-Specific Factors In The Determination Of Emerging Market Debt Spreads", Policy Research Working Paper Series 3626, The World Bank, (2005).

Engle, R. F., "Autoregressive conditional heteroscedasticity with estimates of the variance of the U.K. inflation", Econometrica, (1982), 50, 987–1008.

Engle, R.F., and R. Susmel, "Common volatility in international equity markets", J. Bus. Econ. Stat., (1993), 11, 167–176.

Engle, R., and K. Kroner, "Multivariate simultaneous generalized ARCH", Econometric Reviews, (1995), 11, 122–150.

Ewing, B. T., F. Malik, and O. Ozfidan, "Volatility Transmission in the Oil and Natural Gas Markets", Energy Economics, (2002), 24, 525–538.

Frankel J., and N. Roubini, "The Role of Industrial Country Policies in Emerging Market Crises", (2001), NBER W P No. 8634.

French, K., G. Schwert and R. Stambaugh, “Expected Stock Returns and Volatility”, Journal of Financial Economics, (1987), 19, 3-29.

Hamao, Y., R.W. Masulis, and V. Ng, “Correlations in price changes and volatility across international stock markets”, Rev. Financ. Stud., (1990), 3, 281–307.

Hamilton, J. D., and R. Susmel, “Autoregressive conditional heteroskedasticity and changes in regime”, Journal of Econometrics, (1994), 64, 307–333.

Hassan, A. A., and F. Malik, “Multivariate GARCH Modeling of Sector Volatility Transmission”, The Quarterly Review of Economics and Finance, (2007), 47, 470–480.

Inclan, C., and G. C. Tiao, “Use of Cumulative Sums of Squares for Retrospective Detection of Changes of Variance”, Journal of the American Statistical Association, (1994), 89, 913-923.

Karolyi, A., “A multivariate GARCH model of international transmission of stock returns and volatility”, J. Bus. Econ. Stat., (1995), 13, 11–25.

Kearney, C., and A. J. Patton, “Multivariate GARCH modeling of exchange rate volatility transmission in the European monetary system”, Financial Review, (2000), 41, 29–48.

King, M.A., and S. Wadhwani, “Transmission of volatility between stock markets”, Rev. Financ. Stud., (1990), 3, 5–33.

Lamoureux, C., and W. Lastrapes, “Persistence in variance, structural change and the GARCH model”, Journal of Business and Economic Statistics, (1990a), 8**,** 225–234.

Lamoureux, C., and W. Lastrapes, “Heteroskedasticity in Stock Return Data: Volume versus GARCH Effects”, Journal of Finance, (1990b), 45, 221-229.

Lastrapes, W., “Exchange rate volatility and U.S. monetary policy: an ARCH application”, Journal of Money, Credit and Banking, (1989), 21, 66–77.

Lin, W., R. F. Engle, and T. Ito, “Do bulls and bears move across borders? International transmission of stock returns and volatility”, Rev. Financ. Stud., (1994) 7, 507–538.

Lunde, A., and P. R. Hansen, “A forecast comparison of volatility mdoels: does anything beat a GARCH(1,1)?”, Journal of Applied Econometrics, (2005), 20.7, 873-889.

Malik, F., B.T. Ewing and J. Payne, “Measuring Volatility Persistence in the Presence of Sudden Changes in the Variance of Canadian Stock Returns”, Canadian Journal of Economics, (2005), 38.3, 1037-1056.

Pagan, A., “The Econometrics of Financial Markets”, Journal of Empirical Finance, (1996), 3, 15-102.

Pagan, A., and G. Schwert, “Alternative Models for Conditional Stock Volatility”, Journal of Econometrics, (1990), 45, 267-290.

Poterba, J.M. and L. Summers, “The persistence of volatility and stock market fluctuations”, American Economic Review, (1986), 76, 1143–51.

Sansó, A., V. Aragó and J.L. Carrion “Testing for Constant Variance in Financial Time Series”, Revista de Economía Financiera, (2004), 4, 32-53.

Tanizaki, H., “Volatility Transmission between Japan, U.K. and U.S. in Daily Stock Returns”, Empirical Economics, (2008), DOI: 10.1007/s00181-007-0182-x.

Weigel, D. D., and G. Gemmill, “What Drives Credit Risk in Emerging Markets? The Roles of Country Fundamentals and Market Co-movements”, Journal of International Money and Finance, (2006), 25, 476-502.

Xu, X. E., and H. G. Fung, “Cross-market linkages between U.S. and Japanese precious metals futures trading”, Int. Fin. Markets, Inst. And Money, (2005),15, 107-124.